A Study on Efficient Receiver Design for UWA Communication System

A Thesis submitted in partial fulfillment of
the requirements for the degree of

Master of Technology
in
Electronics and Communication Engineering
Specialization: Communication and Network

By

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Rourkela, Odisha, 769 008, India

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Certificate

This is to certify that the thesis work entitled “A Study on Efficient Receiver Design for UWA Communication System” submitted by Pragya Bharti (Roll No 214EC5186) in partial fulfillment of the requirements for the award of the degree of Master of Technology in Electronics and Communication Engineering (Communication and Networks), National Institute of Technology, Rourkela is an original research work carried out under my supervision and guidance. Neither this thesis nor any part of it, to the best of my knowledge, has been submitted for any degree or academic award elsewhere.

Place: NIT Rourkela
Date: 27th May 2016

Dr. S. Deshmukh
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Declaration

I certify that

1. The work done in this thesis is original and completed by me under the guidance of my supervisor.
2. This work has not been submitted to any other Institute for any degree.
3. I gave credit to any material used from any other sources by citing them and giving their details in the reference.
4. Whenever I have quoted written materials from other sources, I have put them in quotation marks and given due credit to the sources by citing them and giving required details in the reference

Pragya Bharti

27th May 2016

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Abstract

Underwater Acoustic Channels are fast varying channel according to environmental conditions and exhibit strong random fluctuations in amplitude as well as phase due to reflection, refraction, and diffraction. Due to these highly space, time and frequency dependent channel characteristics, it is very difficult to establish reliable and long-range underwater acoustic communication. In this project, channel modeling has been done showing the different channel characteristics of underwater and their dependencies on frequency, temperature, pressure, salinity etc. Also, it has been shown through some theoretical and practical results that the nakagami fading is the best suitable generalized fading to be used in underwater. In this research work various techniques such as equalization, pilot based OFDM and LDPC Coding has also been done to mitigate the channel fading effect and to improve the performance. An adaptive equalizer has been implemented through three different algorithms LMS, NLMS and RLS for linear as well as non-linear channels to mitigate ISI and, their convergence characteristics along with bit error rate performance has been compared. Two types of pilot insertion, block and Comb type has also been done while implementing OFDM.

Block type pilot based OFDM is suitable for slow fading and comb type pilot based OFDM is suitable for a fast fading channel. As in underwater, both types of fading exist, hence, lattice type pilot based OFDM is the best suitable for underwater acoustic communication. LDPC channel coding through which almost Shannon capacity performance can be achieved; has also been implemented taking nakagami channel fading. Bit error rate performance has been compared for different LDPC decoding techniques and for different code rate.

Keywords: LDPC, OFDM, LS, MMSE, Nakagami

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Abbreviations

AWGN	Additive White Gaussian Noise
BPSK	Binary Phase Shift Keying
CP	Cyclic Prefix
DFE	Decision Feedback Equalizer
DFT	Discrete Fourier Transform
DR-LMS	Data Rate Least Mean Square
DSL	Digital Subscriber line
EM	Electromagnetic Wave
IDFT	Inverse Discrete Fourier Transform
ISI	Intersymbol Interference
LAN	Local Area Network
LDPC	Low-Density Parity Check
LL	Log-likelihood
LMS	Least Mean Square
LS	Least Square
MIMO	Multi Input Multi Output
MMSE	Minimum Mean Square Error
MSE	Mean Square Error
NLMS	Normalized Least Mean Square
OFDM	Orthogonal Frequency Division Multiplexing
PDF	Probability Density Function
P/S	Parallel to Serial
QAM	Quadrature Amplitude Modulation
QPSK	Quadrature Phase Shift Keying
RLS	Recursive Least Square
SNR	Signal to noise ratio
S/P	Serial to Parallel

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CHAPTER 1

Introduction

1.1 Background

Underwater communication has various applications such as ocean monitoring, underwater exploration, submarine guidelines etc. Wired communication is a reliable way of communication but it has various disadvantages. Cables are heavy and costly and also motion will be restricted to few meters only hence wireless communication will be more efficient. Radio wave undergoes very high attenuation (~m @ 10 kHz) and the optical signal can travel up to short distances only (<100m). Hence, acoustic wave is the only solution but has low bandwidth. Underwater acoustic channel undergoes time and spatial varying distortions. Until 1970's, communication system had not developed any techniques to mitigate such channel fading effects. With the advancement of technology and introduction of digital communication, some techniques were developed for compensating the channel fading effects. There has been steady improvement in data rate and reliability in case of underwater communication. During early 1980's, an incoherent modulation technique such as FSK was introduced and during that time it was believed that phase coherent modulation technique would not work in underwater acoustic channels. But due to higher bandwidth efficiency of phase coherent system, many types of research was done during 1990's. Due to powerful receiver algorithm coupled with decision feedback equalizer, the data rate of up to 10 kbps was achieved in a medium range shallow underwater acoustic channel. Later, 20 kbps was also achieved in a very shallow UWA channel.

1.2 Motivation

The underwater acoustic channel is one of the most difficult media for communication today due to several factors existing in UWA channel such as limited bandwidth and power resources, long delay spread, Doppler spread, multipath fading effect, frequency dispersion, severe attenuation etc. Due to these problems, many challenges arise for efficient communication inside water such as utilizing the limited available bandwidth to achieve high network throughput and also to mitigate the fading effect so as to increase the transmission rate. The background noise present inside water is often characterized as Gaussian but it is not white. Till now, not any generalized noise modeling has been developed. Acoustic propagation is mostly possible at low frequency hence, it cannot travel to greater distances. UWA communication system is wideband as its bandwidth is not negligible w.r.t. center frequency. The channel impulse response can be sparse where each path can be time varying and Doppler spreading and shifting can also occur due to the motion. There are random signal variations due to fluctuations in the sound speed, internal turbulence, surface waves etc. There is no generalized channel model also for UWA and experiments are generally made to study the statistical properties of the channel. In spite of all the above challenges, several techniques have to be developed to make the UWA communication almost as efficient as radio wireless communication.

1.3 Challenges addressed

Due to the multipath fading of time dispersive acoustic channel, ISI occurs. ISI effect has been compensated through equalizer which acts as a filter at the receiver and has the impulse response as the inverse of the channel impulse response. To achieve high data rate in case of the highly dispersive acoustic channel, OFDM in the form of multicarrier modulation has been used. In OFDM, cyclic prefix and pilot insertion is done. CP removes the ISI effect and pilot is inserted to eliminate the slow and fast fading effect using block and comb type pilot respectively. OFDM increases the data rate of transmission and improves the bit error rate performance. Using OFDM, transmission range of 2.5 km with bandwidth 22-46 kHz can be achieved. The underwater environment is very complicated, it is dispersive in time as well as frequency. Hence, the key technology to mitigate the effect of strong interference and fading of the acoustic signal is to ensure the valid and reliable transmission. Hence, channel coding has also been used. LDPC code is a linear error correcting code and is the best coding for transmission over the noisy channel. The performance close to Shannon capacity can be achieved through this.

1.4 Objective of the work

The Objective of the research work can be given as follows:

- Study the underwater acoustic channel behavior and find the best suitable channel fading for underwater.
- Implement the equalizer with different algorithm taking the above channel fading and analyze the performance by varying the channel fading parameter.
- Implement OFDM with comb and block type pilot pattern and estimate the channel, taking the value of channel parameter as that for underwater channel.
- Implement LPDC channel coding taking the nakagami channel fading and compare

the performance for different fading extent and also implement different LDPC decoding techniques.

1.5 Thesis Organization

This thesis comprises of 6 chapters. In the current chapter introduction to underwater acoustic communication, the objective of the project and motivation towards it are discussed. Rest chapters consists of following details:

Chapter-2 Channel Modelling

In this chapter, there are brief discussions about channel parameters such as speed of sound, acoustic intensity loss, depth and shallow reflections, propagation delay etc. has been discussed. Multipath channel model and channel fading characteristics have also been discussed.

Chapter-3 Equalization

In this chapter, various equalization algorithms such as LMS, NLMS, and RLS has been discussed and learning curve as well as bit error rate performance has been compared, taking fading as nakagami fading . Also, it has been found that which equalization algorithm is the best suitable algorithm.

Chapter-4 Pilot Based OFDM

Three different types of pilot can be used in OFDM. In this chapter, Block and comb type pilot based OFDM has been implemented and it has been analyzed that lattice type pilot based OFDM is the best for time as well as frequency dispersive underwater acoustic channel.

Chapter-5 LDPC channel coding

In this chapter, LDPC channel coding has been implemented by taking nakagami channel fading and the bit error rate performance has been compared for different fading extent and for different decoding algorithms (hard and soft decision).

Chapter-6 Conclusion and Future Work

The thesis ends with this chapter. In this, conclusion and future work have been derived.

CHAPTER 2

Channel Modelling

2.1 Introduction

Underwater acoustic propagation is basically characterized by three main factors: multipath propagation varying with time, frequency dependent signal attenuation and also very low speed of sound i.e. 1500 m/s. Noise is also not Gaussian and has decaying power spectral density [2]. Acoustic propagation only takes place at low frequencies of 10 to 15 kHz and has very low bandwidth of approximately 5 kHz. Delay spread of the order of almost hundreds of millisecond creates frequency selective distortion and motion creates extremely high Doppler Effect [1, 3]. Hence, many efficient techniques have to be used for underwater communication. But before that, channel modeling should be done. In this chapter, many channel characteristics such as speed of sound, acoustic intensity loss, reflection, propagation delay, channel fading etc. have been discussed and also their dependencies on various parameters such as frequency, temperature, pressure, salinity etc. has been analyzed [26]. As acoustic channel has a large range of fading extent hence, nakagami fading is the best suitable as it is a generalized type of fading [4]. Theoretically, there are three different metric measures to know the best suitable fading distribution for any particular practical scenario.

2.2 Channel Parameters

2.2.1 Speed of Sound

The Sound speed in the ocean varies slightly. Normally, the Sound speed C takes values in between 1440 and 1550 m/s. But, slight variations in the speed has also the serious impact on the sound propagation in the ocean/water. The sound speed depends on temperature$T$, depth z or pressure P and salinity S. The following equation is a simple equation to calculate speed of sound but it is not so accurate and can be given as:

$$C = 1449.2 + 4.6\,T - 0.055\,T^2 + 0.00029\,T^3 + (1.34 - 0.010\,T)(S-35) + 0.016z \quad (1.1)$$

Where T is the temperature in ℃

S is salinity in ppm [‰]

z is depth in meters and

C is the sound speed in m/s

2.2.2 Acoustic Intensity Loss

The intensity of acoustic wave propagating through the ocean is weakened by mainly two phenomena, absorption, and spreading.

Spreading losses are mainly caused by the geometric propagation of acoustic wave far away from the source. Basically, two geometrical phenomena can be observed in acoustic underwater propagation: spherical and cylindrical geometry. In a homogeneous medium, the source transmits power in all directions. This phenomenon is known as spherical spreading.

Weakening of acoustic signal because of spherical spreading can be calculated as

$$a_{sphere}\,(\mathrm{r}) = \left[\frac{I_o}{I}\right]_{sphere} = \left[\frac{r}{r_o}\right]^2$$

Hence, in case of spherical spreading, intensity is inverse function of r^2.

When the propagation medium is restricted between two reflecting planes then the sort of spreading is called cylindrical spreading. The separation between these two reflecting planes must be more than almost ten times the wavelength.

Weakening of acoustic signal caused be cylindrical spreading can be given as:

$$a_{cylindrical}\,(\mathrm{r}) = \left[\frac{I_o}{I}\right]_{cylindrical} = \left[\frac{r}{r_o}\right]$$

The loss due to spreading (in dB) is calculated by the following formula:

$$PL_{spreading} = \mathrm{k} \times 10 \log(\mathrm{r})$$

$PL_{spreading}$ is the path loss expressed in dB. r is the transmission range.

k (spreading factor) (k=1 for cylindrical spreading and k=2 for spherical spreading)

Let h_1 be the transmitter depth, h_2 be the receiver depth, h the water depth and D be the transmission range.

The direct distance between transmitter and receiver D_{00} can be given by:

$$D_{00} = \sqrt{D^2 + (h_1 - h_2)^2}$$

Let D_{sb} be the distance between transmitter and receiver in which first reflection of signal is on the surface, here, s denotes reflections on the surface whereas b denotes reflections through the bottom of the ocean:

$$D_{sb} = \sqrt{D^2 + [2bh + h_1 - (-1)^{s-b} h_2]^2}$$

Whereas, D_{bs} be the distance between transmitter and receiver where signal first gets reflected through the bottom of the ocean.

$$D_{bs} = \sqrt{D^2 + [2bh + h_1 - (-1)^{s-b} h_2]^2}$$

When sound gets propagated through the water, some amount of acoustic energy gets converted into heat i.e. it gets absorbed continuously. The absorption is basically due to liquid viscosity, mainly between the frequency range of 100 Hz and 100 kHz. Sound intensity can also be attenuated due to the phenomenon of scattering of sound waves due to inhomogeneity. Sound attenuation is the combined effect of scattering and absorption.

The attenuation Coefficient β [dB/km] between frequencies range of 3 kHz and 500 kHz can be calculated using following formula [17]:

$$\beta = 8.68 \times 10^3 \left(\frac{SAf_T f^2}{{f_T}^2 + f^2} + \frac{Bf^2}{f_T} \right)(1 - 6.54 \times 10^{-4} P)$$

Where A= 2.35$\times 10^{-6}$, B= 3.375$\times 10^{-6}$

Here, S is the salinity, P is the hydrostatic pressure in kg/cm^2 and f is the frequency of acoustic wave in kHz.

f_T is the relaxation frequency in kHz.

$$f_T = 21.9 \times 10^{6-1520/(T+273)}$$

The frequency at which the dielectric loss factor reaches a maximum is called Relaxation frequency f_T.

Between 100 Hz and 3 kHz frequency, β can be found by the following thorp's formula:

$$\beta = \frac{0.11f^2}{1+f^2} + \frac{44f^2}{4100+f^2}$$

The attenuation of the sound wave at low frequencies is not that much. At a very low frequency of 100 Hz, the intensity of the sound wave decreases to only one-tenth of its previous value after traveling over many thousands of km also. In ocean environment, the low-frequency sound wave is best for transmission as compared to any other type of radiation. EM waves are completely absorbed in a very few distance of 1 km only. The absorption coefficient is calculated through the value of temperature, pressure and salinity and hence maximum distance of propagation is decided. Absorption coefficient greatly depends on salinity. Above 200 kHz frequency, an increase in salinity by 5 ppm results in an increase of attenuation coefficient by10 dB/km. Temperature does not have more effect on β. Below 200 kHz, upon increasing temperature, β decreases, but above 200 kHz reverse happens. On the basis of attenuation coefficient, sound pressure loss (scattering loss factor) at any distance D from the source can be found as:

$$L_A(\mathrm{D}) = 10^{-[(D/1000)\beta]/20}$$

2.2.3 Depth and Shallow Reflections

While propagating through the ocean, the sound wave gets reflected through rough surfaces and it creates reflected field with coherent and incoherent components. The wave that propagates along the direction of reflection is called coherent component. As the wave is not totally reflected, some portions are lost; incoherent components takes these into account. Hence, the reflection coefficient is less than one and it decreases as the height of the imperfections on the surface increases. Ocean surface only reflects the incident sound wave while the seabed surface reflects as well as absorbs the incident wave. When acoustic wave incident on the seabed then some part of acoustic energy gets penetrated into the soil and that's why at low frequencies, sound propagation distance is smaller. The reflection coefficient through the seabed surface depends on the granularity as well as the density of the particles forming the seabed. Assuming that the seabed is smooth, the reflection coefficient depending on the angle of incidence through the bottom of the sea is as below:

$$L_{BR}(\theta) = \left|\frac{m\cos\theta - \sqrt{n^2 - \sin^2\theta}}{m\cos\theta + \sqrt{n^2 - \sin^2\theta}}\right| ,$$

Where m= $\frac{\rho_1}{\rho}$, n= $\frac{c}{c_1}$, where c and ρ respectively denote the speed and density of sound in sea water. Whereas c_1 and ρ_1 represent speed and density of sound in sea bottom surface.

Let θ_{sb} be the incident angle through D_{sb} and θ_{bs} be the incident angle through D_{bs}, then,

$$\theta_{sb} = \tan^{-1}\left(\frac{D}{2bh + h_1 - (-1)^{s-b} h_2}\right)$$

$$\theta_{bs} = \tan^{-1}\left(\frac{D}{2bh - h_1 + (-1)^{s-b} h_2}\right)$$

As the characteristics of seabed cannot be found easily hence it is not possible to obtain coherent parameter values hence coherent reflection coefficient cannot be calculated.

2.2.4 Propagation Delay

Propagation delay occurs due to the differences between path lengths. Let τ_{sb} be the propagation delay along the path D_{sb} and τ_{bs} be the propagation delay along the path D_{bs}. So, we have

$$\tau_{sb} = \frac{D_{sb} - D_{00}}{c}$$

$$\tau_{bs} = \frac{D_{bs} - D_{00}}{c}$$

The propagation delays of the different signal path with respect to the line of sight path are an important parameter for the underwater acoustic channel. Due to the signal arriving with some delay at the receiver intersymbol interference (ISI) occurs which affects the system performance and the transmission rate also reduces.

2.3 Multipath Channel Model

We studied all the channel parameters and its mathematical formulation which affect the acoustic signal propagation in a non-varying channel. Hence, the combined effect of all those parameters is as below.

Let x (t) be the transmitted signal through the channel and y (t) the received signal.

$$y(t) = \frac{L_A(D_{00})}{D_{00}} x(t) + \sum_{S=1}^{\infty} \sum_{b=S-1}^{S} \frac{L_A(D_{Sb})(L_{SR})^S \left(L_{BR}(\theta_{Sb})\right)^b}{D_{sb}} x(t - \tau_{Sb})$$
$$+ \sum_{b=1}^{\infty} \sum_{S=b-1}^{b} \frac{L_A(D_{bS})(L_{SR})^S \left(L_{BR}(\theta_{bS})\right)^b}{D_{bS}} x(t - \tau_{bS})$$

2.4 Channel Fading Characteristics

Channel Fading Characteristics can be obtained through three different metrics. First of all, data are collected through different experiments performed at different places and histogram of signal level is plotted. After that, the signal level histogram is divided into 100 bins. Now, P is the probability distribution of the measurements, Q is the probability distribution of the fading which we want to check for fit.

The first metric is kullback- Leibler divergence D_{KL} , defined as

$$D_{KL}(P||Q) = \sum_i P(i) \log_2 \frac{P(i)}{Q(i)}$$

The Second metric is the Bhattacharya distance D_B , defined as

$$D_B(P, Q) = -\log_2(BC)$$

Where BC is the Bhattacharya coefficient, $\sum_i \sqrt{P(i)Q(i)}$.

The third and last metric, D_{CRM}, is Bhattacharya coefficient metric, proposed by Comaniciu, Ramesh, and Meer and is defined as

$$D_{CRM}(P, Q) = \sqrt{1 - BC}$$

Following table provides the values of the three metrics and the log-likelihood (LL) values obtained while fitting the distributions to the data. For each of the 3 metrics, a lower value indicates less divergence from the actual data. Following metric measures were obtained through two experiments which were performed at two distances 505m and 200m. The channel was approximately 3m deep. The transmitter was located 1m inside the water surface; hydrophones were located 60cm below the water surface.

Each test consisted of transmitting a combined signal which contains 5 sinusoidal components -85, 75, 60, 45, 30 kHz.

Goodness of Fit (505m)

	D_{KL}	D_B	D_{CRM}	LL
Beta	0.0439	0.0038	0.0514	3.14567 e+007
Gamma	0.0471	0.0041	0.0533	3.14472 e+007
Lognormal	0.3689	0.0212	0.1208	3.07398 e+007
Nakagami-m	0.0263	0.0037	0.0506	3.13736 e+007
Rayleigh	0.0413	0.0052	0.0600	3.13174 e+007
Rice	0.0413	0.0052	0.0600	3.13174 e+007

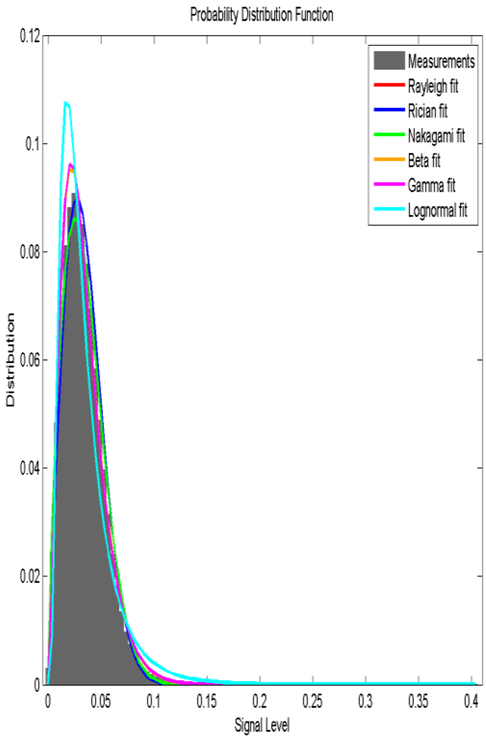
Goodness of Fit (200m)

	D_{KL}	D_B	D_{CRM}	LL
Beta	0.0328	0.0083	0.0755	1.43424 e+007
Gamma	0.0529	0.0136	0.0967	1.41509 e+007
Lognormal	0.1803	0.0376	0.1604	1.30297 e+007
Nakagami-m	0.0100	0.0026	0.0422	1.45294 e+007
Rayleigh	0.0100	0.0026	0.0424	1.45291 e+007
Rice	0.0069	0.0016	0.0336	1.45580 e+007

In the case of 505-meter, all three metrics measure says that the nakagami-m distribution with m=0.889274 was the most suitable fading distribution as it has the lowest value means lower deviation from the real data. In the case of 200- meter, the nakagami distribution has a value of parameter m=1.00845. The rician distribution was the most suitable distribution as it has the lowest value through all three metric.

In the case of 200 meters, there is a stronger line of sight component described by the rician model. In the case of 505 meters, as the value of m in nakagami-m distribution is less than one hence it appears to be worse than Rayleigh fading.

Following figures shows the histograms obtained through the measurements and the pdf for each of the 6- distributions for the 505-meter and 200-meter channels respectively.



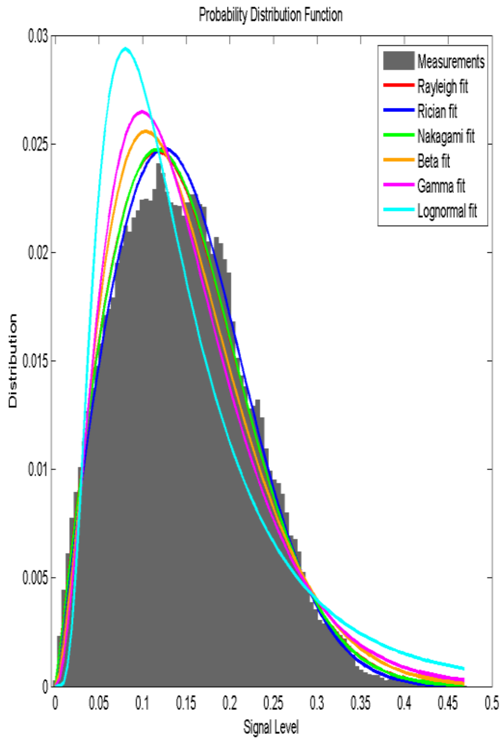


Fig 2.1 PDF of distributions at 505 meter   Fig 2.2 PDF of distributions at 200 meter

There are different channel parameters which affect the transmission inside the water. Also, the different metrics are used to find the type of fading that exist in different environmental conditions. But, in a generalized way we can use the nakagami fading as we can set the different value of the parameter (m) which defines the different extent of fading.

2.4.1 Nakagami Fading

Nakagami fading has become an interesting research area wireless communication. In underwater acoustic communication also, nakagami fading is the best fading to be used as the acoustic channel has a large extent of variation. Nakagami-m distribution is the best fit distribution according to the measured data over a wide frequency range. PDF of the signal with nakagami-m distribution can be given as-

$$f(x) = \frac{2}{\tau(m)} \left(\frac{m}{\Omega}\right)^m x^{2m-1} e^{-mx^2}/_{\Omega}$$

Where x≥ 0, m≥ 0.5, Ω≥ 0

$\tau(.)$ represent the gamma function

$m = E^2(x^2)/var(x^2)$ is the shape parameter which determines that how severe is the fading.

m= 1, Rayleigh fading

$$\Omega = E(x^2)$$

$$\tau(m) = \frac{x^{2m}}{\sigma^m} \text{ and } \sigma = \frac{x^2}{m}$$

2.5 Numerical Analysis and discussion

Fig 2.3 shows the absorption coefficient varying w.r.t. frequency. In the above equation, we can see that the absorption coefficient depends on temperature, pressure as well as salinity.

Now, by putting the constant value of temperature ($T = 15$℃) and pressure (P=1 atm) and by varying the salinity value, we can see how absorption coefficient varies with salinity. It can be seen that at lower frequency there is slight variation due to salinity. But at a higher frequency (i.e. above 200 kHz), if salinity increases by 5 ppm, than absorption/ attenuation coefficient increases by 10dB/km.

Simulation Configuration: $T = 15$℃ , P=1 atm, S = 20, 25, 30, 35 ppm

Fig 2.4 shows the variation of absorption coefficient w.r.t. frequency with varying temperature. The temperature doesn't effect β more as compared to salinity. At low frequencies (less than 200 kHz), the absorption coefficient decreases as temperature increases but above this frequency absorption coefficient increases as temperature increases.

Simulation Configuration: Salinity S= 25 ppm, T= 15, 20, 25, 30 ℃

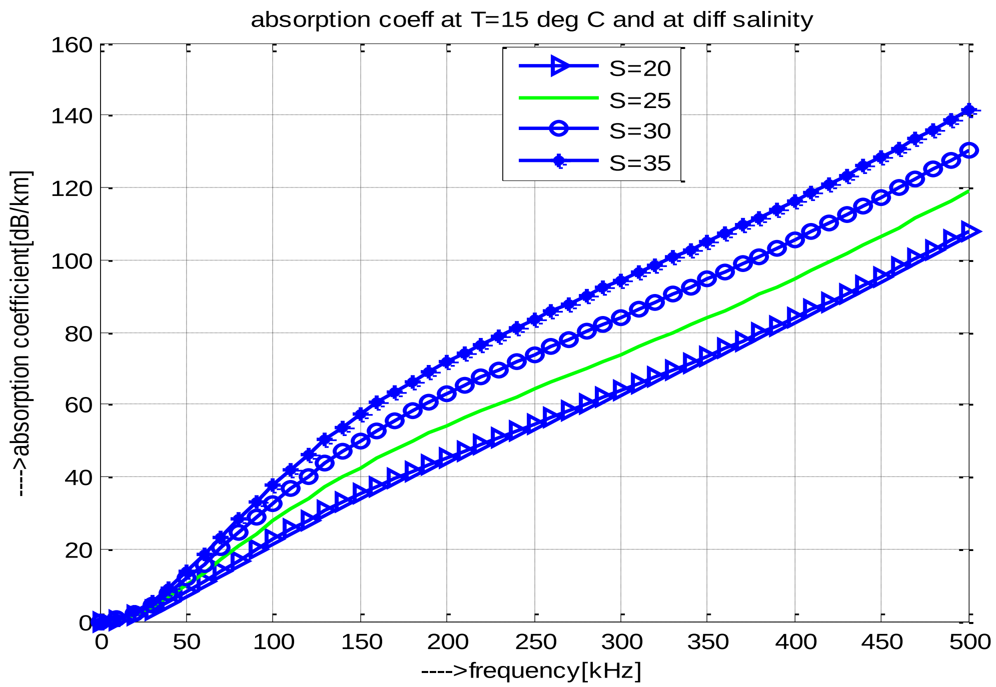


Fig 2.3 Absorption coefficient as a function of frequency for different values of salinity

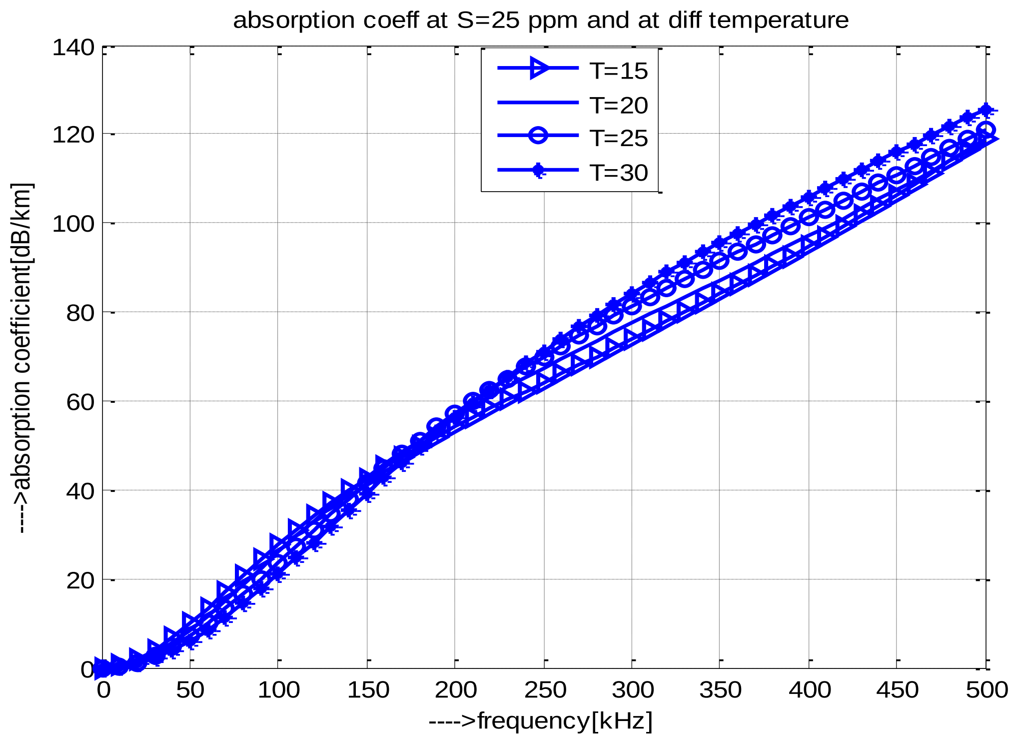


Fig 2.4 Absorption coefficient variation w.r.t. frequency with different temperature values

Fig 2.5 shows the scattering loss factor as a function of frequency. We can see the above equations for scattering loss factor i.e. $L_A(\mathrm{D}) = 10^{-[(D/1000)\beta]/20}$. Here, D is the distance along the transmitted signal from the source. β is the attenuation coefficient as shown above. Now, as β depends on temperature, pressure as well as salinity, scattering loss factor also depends on all these. At low frequency upto 1 kHz, scattering loss is constant and above this there is abrupt decrease in its value.

<u>Simulation Configuration:</u> T= 15 ℃, S= 25 ppm , P= 1.033 atm, D = 20 km

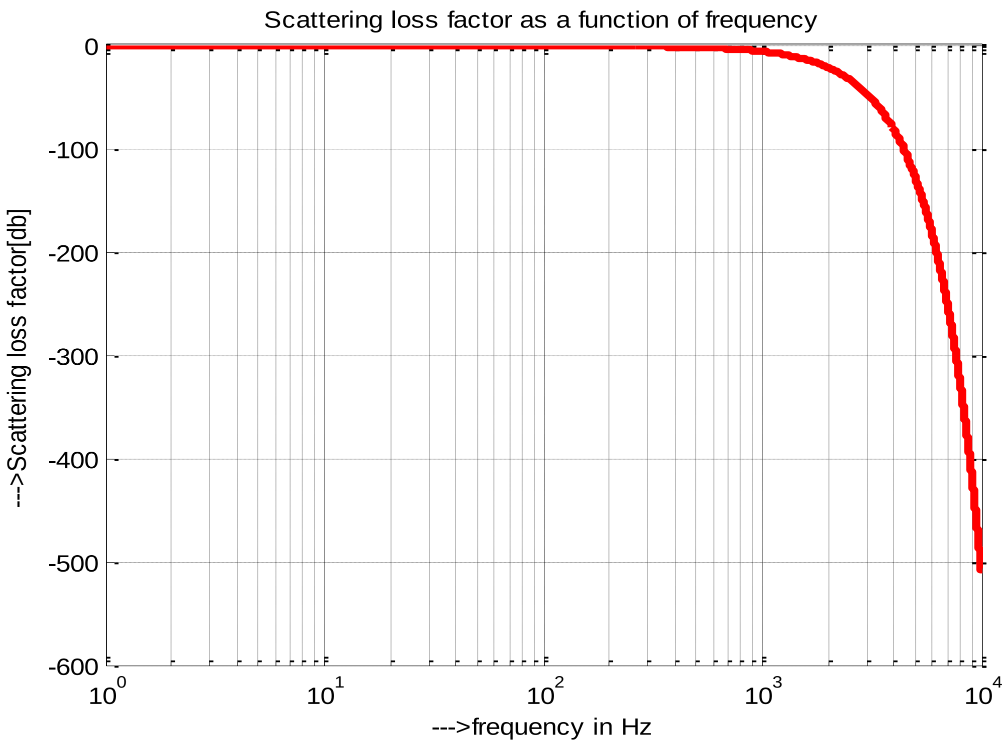


Fig 2.5 Scattering loss factor variation w.r.t. frequency at temperature T=15 ℃ and salinity S=25 ppm and D=50 km

Fig 2.6 shows the reflection coefficient through the seabed varying with the angle of incidence according to the above equation. At the lower grazing angle the reflection coefficient is 1 (i.e. total reflection occurs) and as the angle increases, reflection coefficient decreases. And at a higher value (above 80°), the reflection coefficient becomes very small.

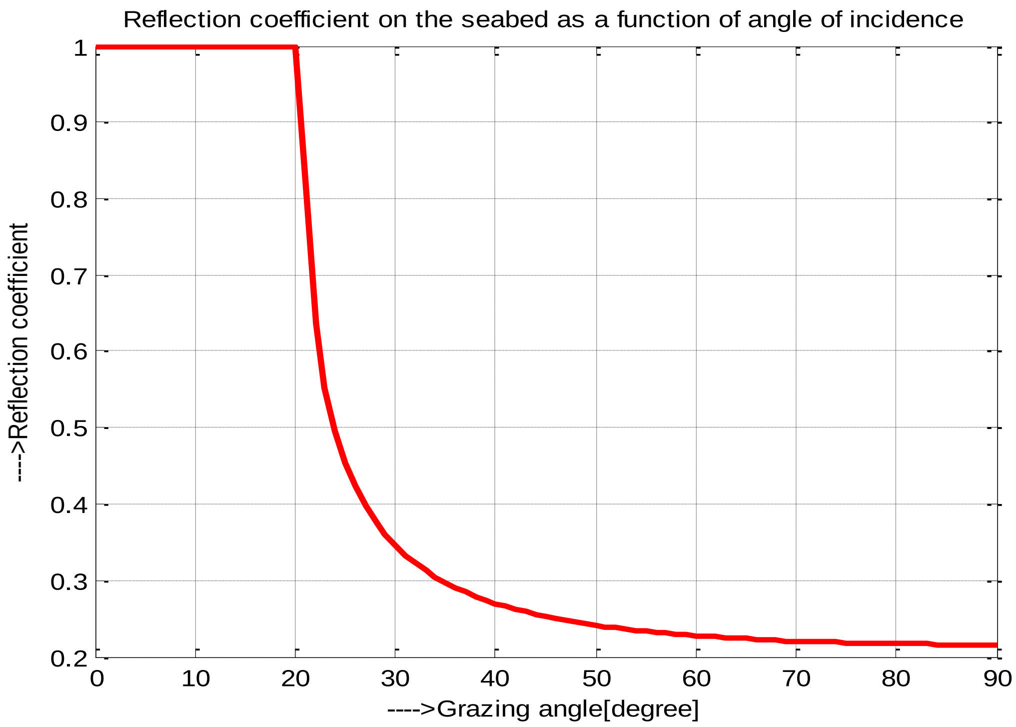


Fig 2.6 Reflection coefficient variation w.r.t. the angle of incidence

2.6 Conclusion

In this chapter, Channel modeling for the acoustic channel has been studied and numerical analysis for different parameters such as Absorption coefficient, scattering loss factor, and Reflection coefficient were analyzed. Also, it has been concluded that nakagami fading will be used for the implementation of all the techniques to be discussed in the following chapters for underwater acoustic communication.

Next chapter will include the implementation of the equalizer.

CHAPTER 3

Equalization

Techniques to mitigate fading effects and increase transmission rate

Due to the adverse effect of fading in the underwater acoustic channel, we use different techniques to compensate fading effect and increase the transmission rate. Also, as the transmission range depends on frequency because the signal attenuation is the function of frequency, we have to use some techniques for efficient bandwidth utilization. Also, equalization can be used to mitigate the channel fading effect. Hence, to increase the overall performance of the system, basically, three techniques can be used in underwater communication. These are as follows:

1. Equalization
2. OFDM
3. Channel Coding

1. Equalization:

Due to the multipath fading of the time dispersive acoustic channel, Intersymbol interference (ISI) occurs. So, equalization can be used to compensate the ISI effect. An equalizer acts as a filter at the receiver side having impulse response to be the inverse of the channel impulse response and it compensates channel amplitude and delay characteristics. It is mainly used in frequency selective fading channels and it tracks the varying channel adaptively.

2. OFDM:

Due to the time and frequency spreading nature of the underwater channel, achieving high data rate in underwater communication is very challenging. Hence, OFDM in the form of multi-carrier modulation technique is the most suitable technique to improve the data rate in the highly dispersive channel. Many techniques can be combined with OFDM for transmission with high data rate and improved bit error rate performance.

3. Channel Coding:

The underwater acoustic environment is very complicated and is dispersive in time, frequency as well as space. We have to develop technology for underwater communication which will overcome the strong fading and interference of the acoustic signals to ensure a reliable data transmission at the low signal-noise ratio. LDPC channel coding is the best suitable for underwater communication. Through LDPC channel coding, performance close to Shannon capacity can be achieved.

3.1 Introduction

To mitigate the channel induced signal distortions, the received signal should be filtered through a structure called equalizer. An equalizer basically consists of delay taps which produce an estimate of the transmitted symbol using the weighted combination of the received signal and also in some cases past symbols [13]. The equalizer performance is measured through the average squared error between transmitted symbol and equalizer output.

As the acoustic channel is random in nature i.e. the channel characteristics keep on varying hence the equalizer for underwater communication should be time varying or adaptive [11]. There are many types of an equalizer which can be used. Basically, two types of equalizer- Linear and decision feedback equalizer has been implemented. There are various algorithms to update the equalizer coefficient adaptively for example- LMS, NLMS, and RLS. There are different implementation aspect, computational complexity, and signal to noise ratio [12].

Statistics of the underwater acoustic channel is not available and also there is not any generalized model for time variation of the channel. The underwater channel is assumed to vary slowly so that the time varying impulse response channel coefficient can be tracked. This assumption enables the use of RLS algorithm for updating of weight coefficient [14, 27]. This algorithm provides a balance between the computational complexity and performance effectiveness. Convergence characteristics and BER are analyzed for performance comparison.

3.2 Equalizer Design

The purpose of equalizer design is to mitigate the ISI effect due to fading and noise. A linear equalizer is basically a filter which reduces the ISI effect. ISI arises due to the overlap of adjacent pulse onto the transmitted pulse. Equalizer acts as the inverse filter at the front end of the receiver and its transfer function is the inverse of the channel impulse response.

Equalization is broadly classified into two categories:

1. **Maximum likelihood sequence estimation (MLSE)**, It uses Viterbi algorithm to equalize the linearly signal transmitted through the dispersive channel. MLSE block processes the input signal and provides the maximum likelihood estimate of that signal using an estimate of the channel.
2. **Equalization with filters,** It uses a filter to compensate the distorted pulse.

Adaptive equalizer comes into the second category of the equalizer and is applied for the time-varying channel.

An Adaptive Equalize operates in two modes: training and tracking

Training Mode:

i. Initially, a training sequence of fixed length is sent through the transmitter so as to average the receiver equalizer to a proper setting.
ii. The training sequence is random or fixed binary signal with some specific bit pattern.
iii. The training sequence is designed such that the equalizer acquires the proper filter coefficient even though the channel condition is worst. A recursive algorithm is used by an adaptive filter to estimate the channel coefficient.

Tracking Mode:

i. After completion of training mode, we get optimal weight coefficient.
ii. Information is sent just after the training sequence.
iii. After the reception of information, equalizer monitors the varying channel through the adaptive algorithm.

3.3 Types of Adaptive Equalizer

There are mainly two types of adaptive equalizer:

1. Linear Equalizer
2. Non-linear Equalizer

3.3.1 Linear Equalizer

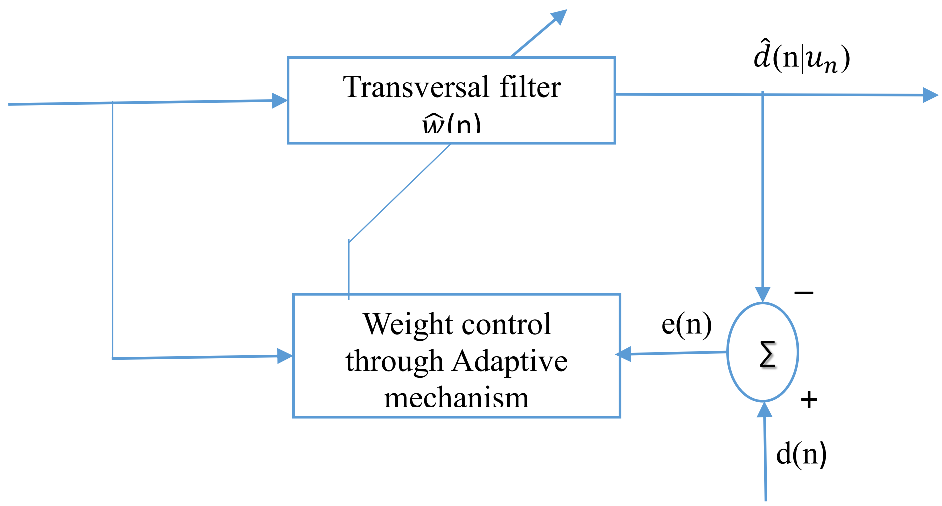


Fig 3.1 Linear Equalizer

Linear Equalizer algorithms

LMS

LMS Algorithm is an important stochastic gradient algorithm. LMS algorithm is very simple algorithm as there is no need to calculate correlation function in this case.

LMS algorithm involves two processes:

1. Filtering Process- When an input signal is applied through a linear filter, the output is generated and through this, estimation error is computed.
2. Adaptive process- Filter parameters automatically adjust its value according to the estimation error.

Hence, LMS algorithm is called adaptive filtering algorithm.

A feedback loop is also there to execute this two processess.

<u>Steps of LMS algorithm:</u>

Parameter: L= Length of filter or no. of taps

μ= step-size

$0 < \mu < \frac{2}{LS_{max}}$, where the value of number of taps, L is moderate to large and the maximum power spectral density of input u(n) is S_{max}.

Initialization: If initial value of the tap-weight vector i.e. $\widehat{w}(0)$ is known then use that value otherwise set that value to zero.

Data: Given u(n) = Tap-input vector at a particular time n having size M×1.

$$= [\mathrm{u(n)}, \mathrm{u(n-1)}, \ldots \ldots \ldots \ldots \ldots, \mathrm{u(n-M+1)}]^T$$

d(n)= desired response at time n

We have to compute $\widehat{w}(n+1) =$ estimate of tap-weight vector at time n+1

Computation:

for n=0,1,2…………M-1

compute e(n)=d(n)- $\widehat{w}^H(n)u(n)$

$$\widehat{w}(n+1) = \widehat{w}(n) + \mu\, u(n)e^*(n)$$

NLMS

The normalized LMS algorithm is same as LMS algorithm but the weight controller mechanism is different than that in LMS. The normalized LMS algorithm exhibits faster convergence rate than LMS algorithm for both uncorrelated and correlated data. The NLMS filter introduces a problem that when the input tap vector u(n) is small, some mathematical difficulties can occur since we have to divide by $||\mathrm{u(n)}||^2$. To overcome this problem one factor whose value is very small δ is introduced to produce:

$$\widehat{w}(n+1) = \widehat{w}(n) + \frac{\tilde{\mu}}{\delta + ||\mathrm{u(n)}||^2}\, u(n)e^*(n)$$

Here $0 < \tilde{\mu} < 2\frac{E[|u(n)|^2]\vartheta(n)}{E[|e(n)|^2]}$ where $E[|e(n)|^2]$ = error signal power

$E[|u(n)|^2]$= input signal power

$\vartheta(n)$= mean-square deviation

RLS

RLS adaptive filter has the rate of divergence faster than simple LMS and NLMS filter. In RLS algorithm, the input data is whitened by the inverse correlation matrix of the data having zero means. But with the performance improvement, computational complexity also increases.

Steps of RLS Algorithm:

Initialization: Set $\hat{w}(0) = 0$ and P(0) = $\delta^{-1}I$

And $\delta = \begin{cases} small\ positive\ constant\ for\ low\ SNR \\ large\ positive\ constant\ for\ low\ SNR \end{cases}$

For each instant of time n=1,2,…………………

Compute $\pi(n) = p(n-1)u(n)$

$$k(n) = \frac{\pi(n)}{\lambda + u^H(n)\pi(n)}$$

$$\varepsilon(n) = d(n) - \hat{w}^H(n-1)u(n)$$

$$\hat{w}(n) = \hat{w}(n-1) + k(n)\varepsilon^*(n)$$

and $p(n) = \lambda^{-1}p(n-1) - \lambda^{-1}k(n))u^H(n)p(n-1)$

Here $\varepsilon(n) = \sum_{i=1}^{n} \beta(n,i)|e(i)|^2$ where e(i) is the difference between the desired response d(i) and the output response y(i).

In RLS algorithm, to better estimate the channel some form of prior information is needed. Hence, the cost function must include a term which will take into account the prior information

$$\varepsilon(n) = \sum_{i=1}^{n} \lambda^{n-i}|e(i)|^2 + \delta\lambda^n||w(n)||^2$$

The first term is the sum of squares of weighted error i.e. data independent.

Second term $\delta\lambda^n||w(n)||^2 = \delta\lambda^n w^H(n)w(n)$ is called regularizing term, where δ is a positive real number called the regularization parameter. This term depends on tap-weight factor w(n) and it stabilizes the solution by smoothing it.

3.3.2 Non-linear Equalizer

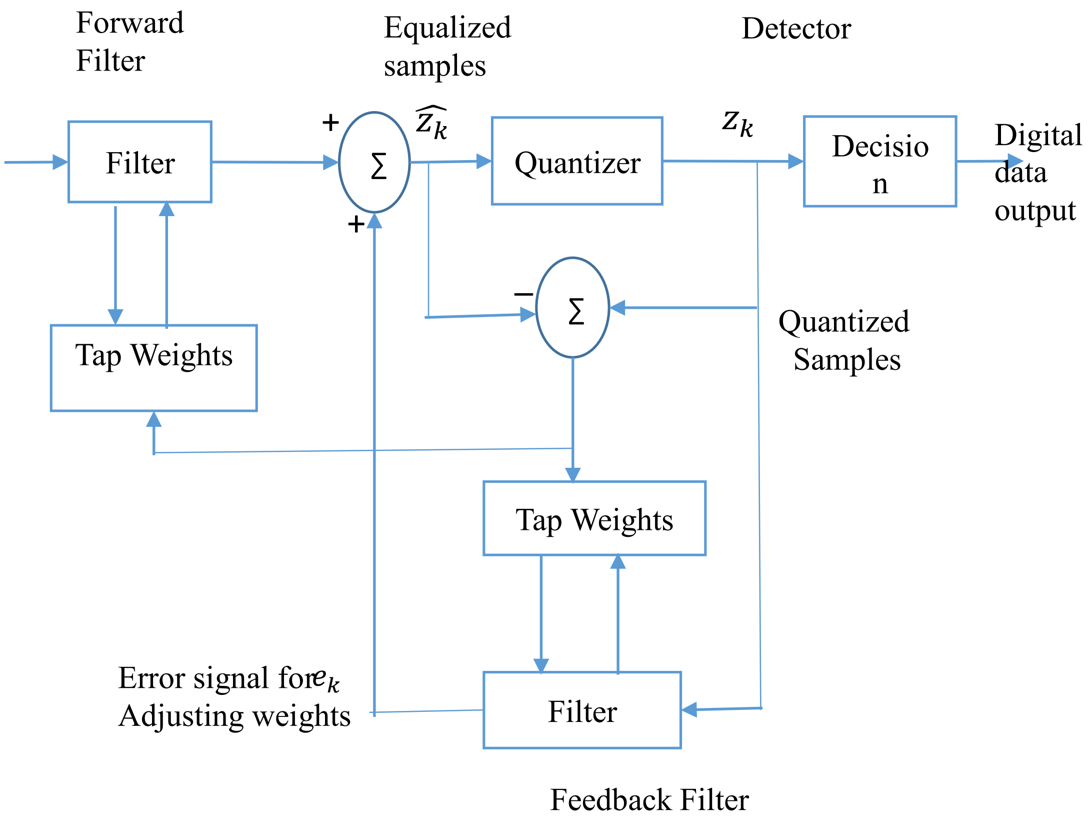


Fig 3.2 Non-linear Equalizer

Decision Feedback Equalizer

There are some limitations of a linear equalizer, for example, transversal filter i.e. it does not perform well whenever there are spectral nulls on the channel. Hence, decision feedback equalizer which is a non-linear equalizer can be used. To eliminate ISI on the current pulse, the previous decision of detector is also used. In this case, the distortions caused by previous pulses on the current pulse is subtracted. In the above figure, the forward and feedback filters are linear filters such as a transversal filter. The main idea behind the decision feedback equalizer is to apply a feedback to the equalized symbol through output such that the previous symbol is known. When the previous symbols through detector are known, the

ISI occurred due to these symbols can be eliminated at the output by subtracting the previous symbol with appropriate weighting. To minimize the MSE (Mean square Error), the tap weights of feedback and forward filter can be changed adaptively. The decision feedback equalizer is useful when the amplitude distortion in the channel is severe but phase offset is small. There is one drawback of DFE structure. If the decision applied to the feedback filter is incorrect, that error propagates to the next few symbols through the feedback filter causing error propagation problem.

3.4 Simulation Results and discussion

Fig 3.3 shows how the learning curve of LMS depends on the parameter step size. Step size is one of the important parameters to be used for weight update. As the step size μ increases the convergence rate of learning curve also increases i.e. the saturation in mean square error is achieved at a lower number of iterations, but one problem is that in case of higher convergence rate mean square error is slightly greater.

Simulation Configuration: Initial weight = 0, Number of iterations = 2000, Step size μ= 0.0035, 0.006, 0.01.

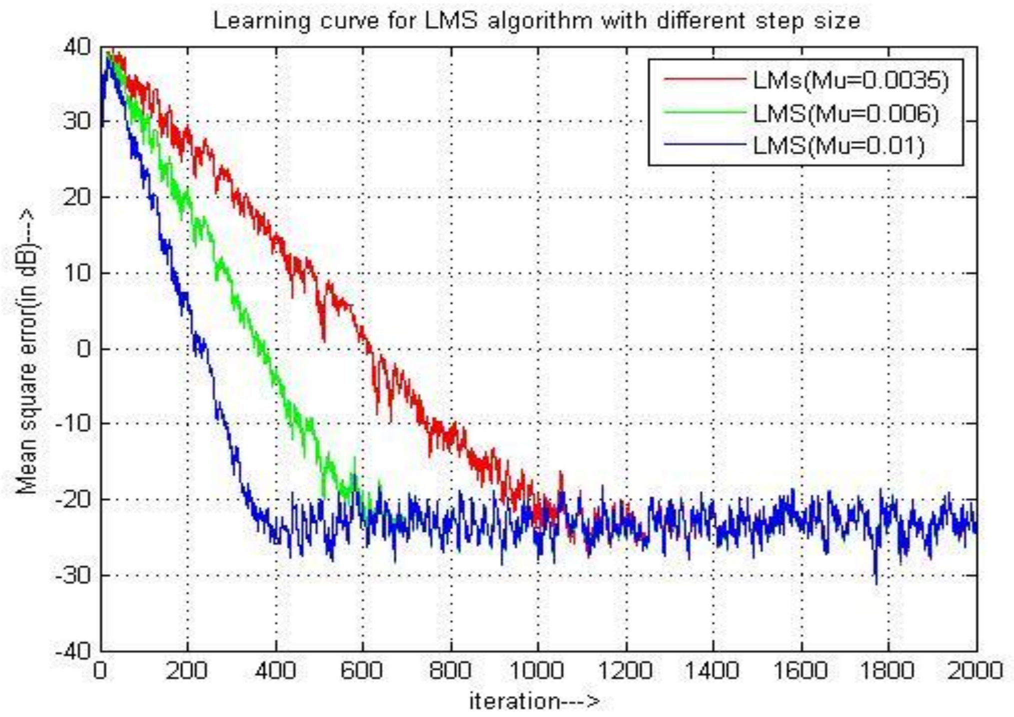


Fig. 3.3 Learning Curve for LMS algorithm having different step size

Fig 3.4 shows the difference between the LMS and NLMS. NLMS algorithm provides convergence characteristics better than that of LMS as NLMS changes the step size at each iteration by dividing with input power. As in the case of NLMS, the step size is divided by the input power, hence in this case step size is taken more than that in LMS. At different step size but at same steady state error, NLMS has better convergence rate than LMS.

<u>Simulation Configuration:</u> Initial weight=0, Number of iterations=1000

Fig 3.5 shows the comparison between RLS and LMS. RLS is an adaptive filter which finds the coefficient recursively and minimizes a weighted least square cost function with respect to the input signals. RLS algorithm has a faster convergence speed. It also has least mean square error than LMS and NLMS.

<u>Simulation Configuration:</u> Initial weight=0, Number of iterations=2000, Step size μ = 0.004

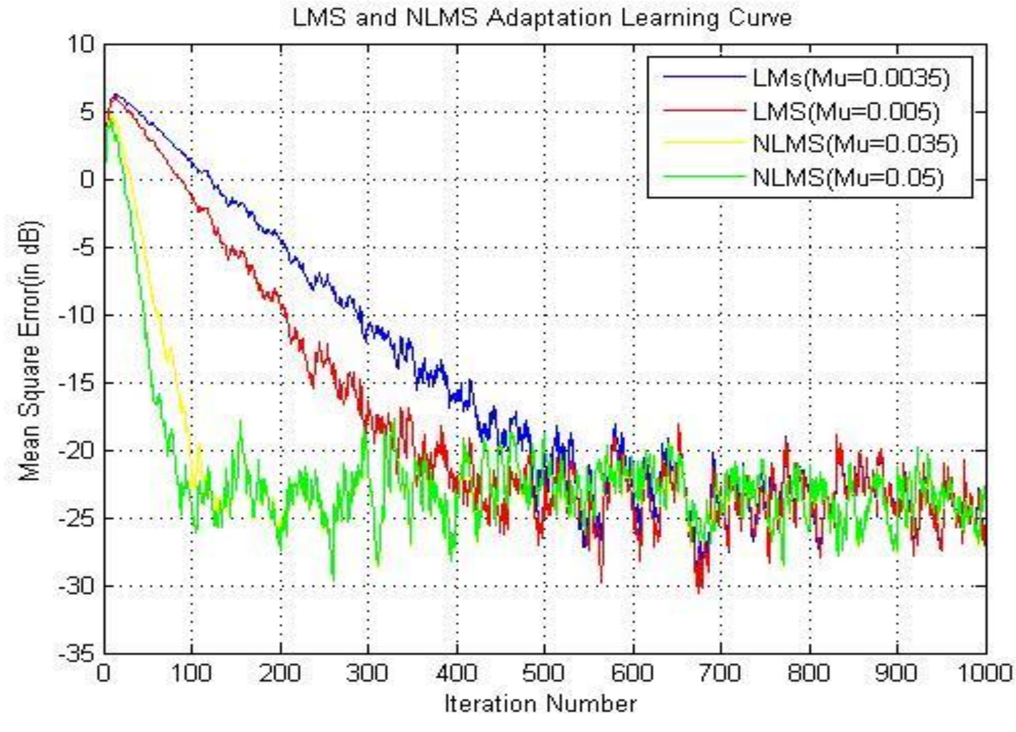


Fig 3.4 Comparison between learning curve of LMS and NLMS

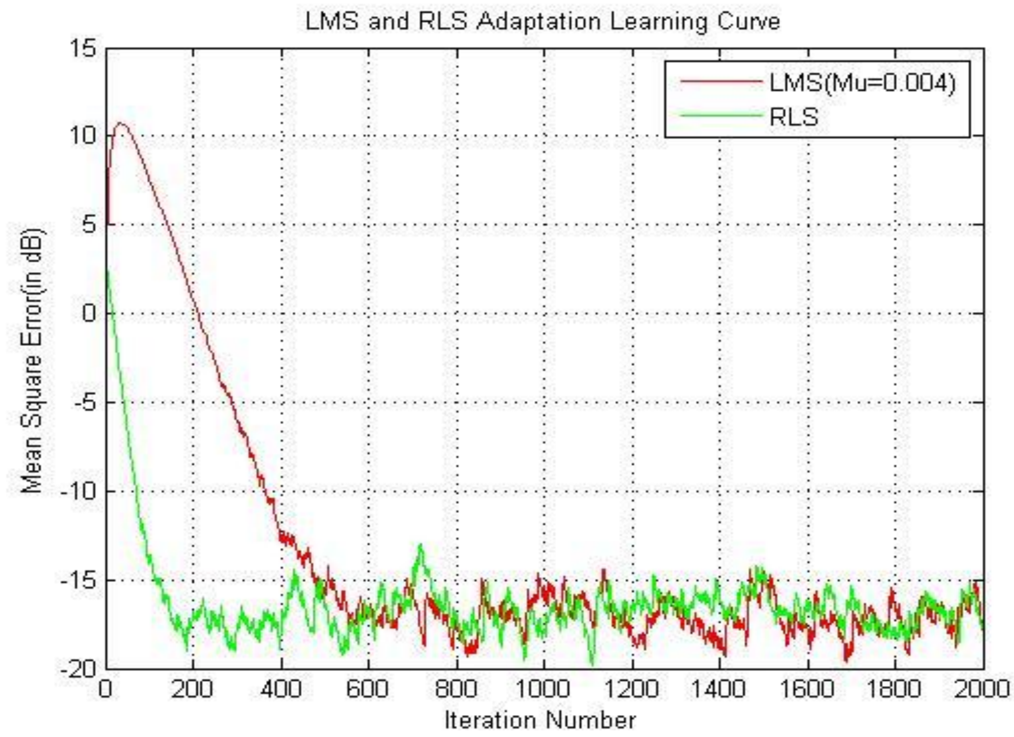


Fig 3.5 Comparison between learning curve of LMS and RLS

Fig 3.6 shows the comparison of a learning curve for LMS algorithm with linear equalizer and LMS with decision feedback equalizer. In LMS with DFE, the constant mean square error is achieved at lower iterations as compared to LMS algorithm in case of linear equalizer. Hence, decision feedback equalizer has better performance than a linear equalizer.

<u>Simulation Configuration:</u> Initial weight=0, Number of iterations=2000, Step size μ = 0.005

Fig 3.7 shows the comparison between learning curve of LMS without and with fading. It can be observed that the in the case of fading mean square error is more. And we know, more error means better convergence. Hence, Learning curve for LMS with fading has better convergence but having more value of mean square error.

<u>Simulation Configuration:</u> Initial weight=0, Number of iterations=2000, Step size μ = 1.2

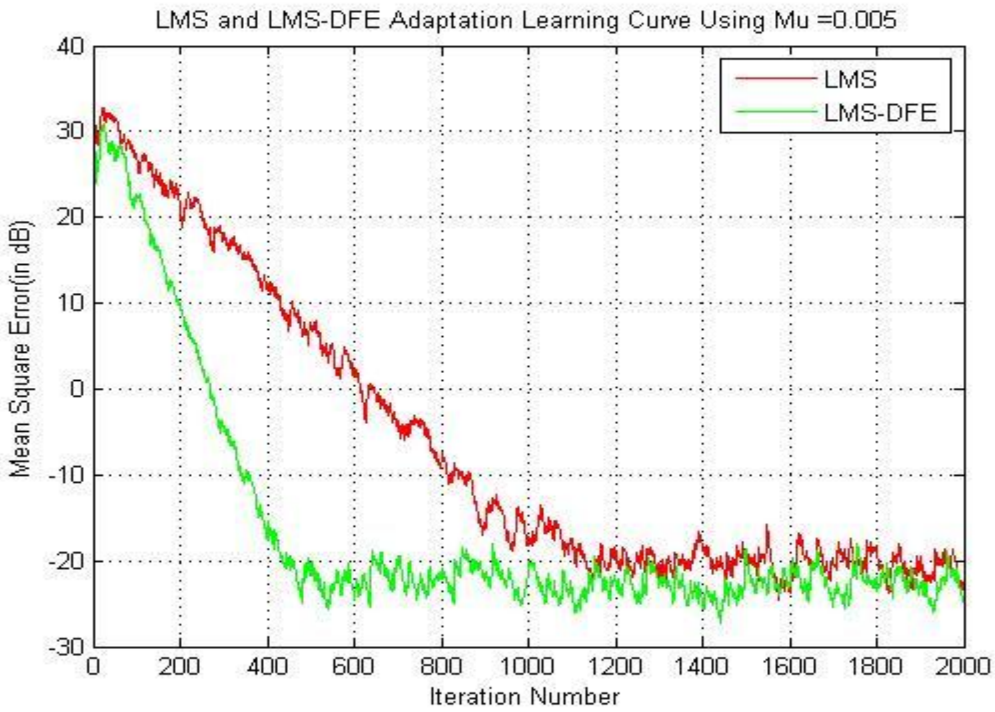


Fig 3.6 Learning curve for LMS with linear equalizer and LMS with DFE

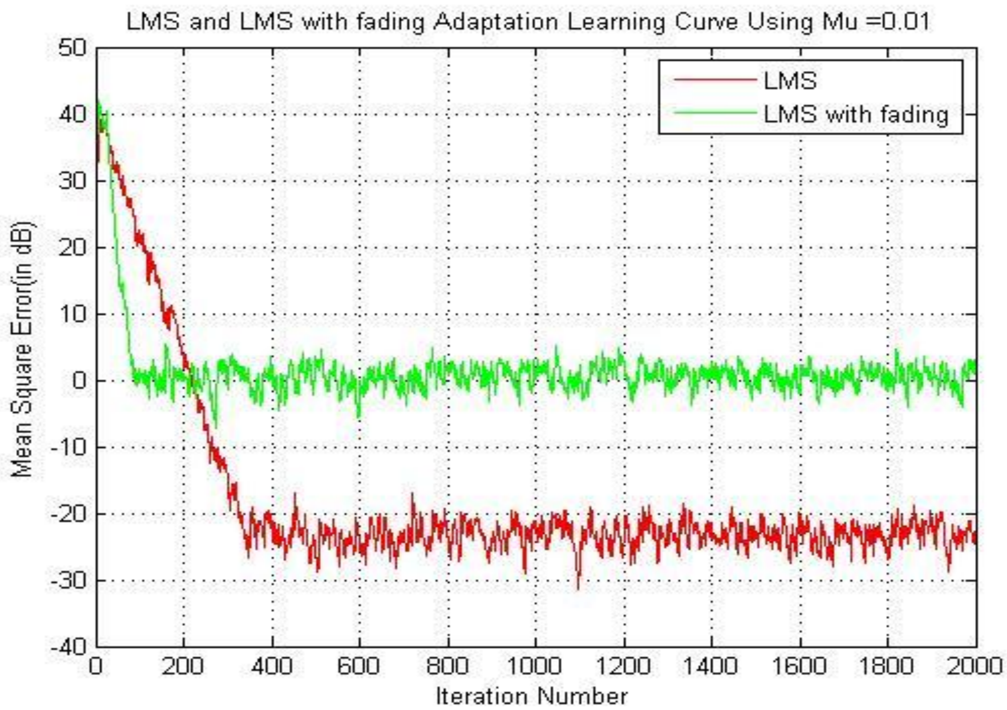


Fig 3.7 Learning Curve performance of LMS without and with fading (m= 1.2)

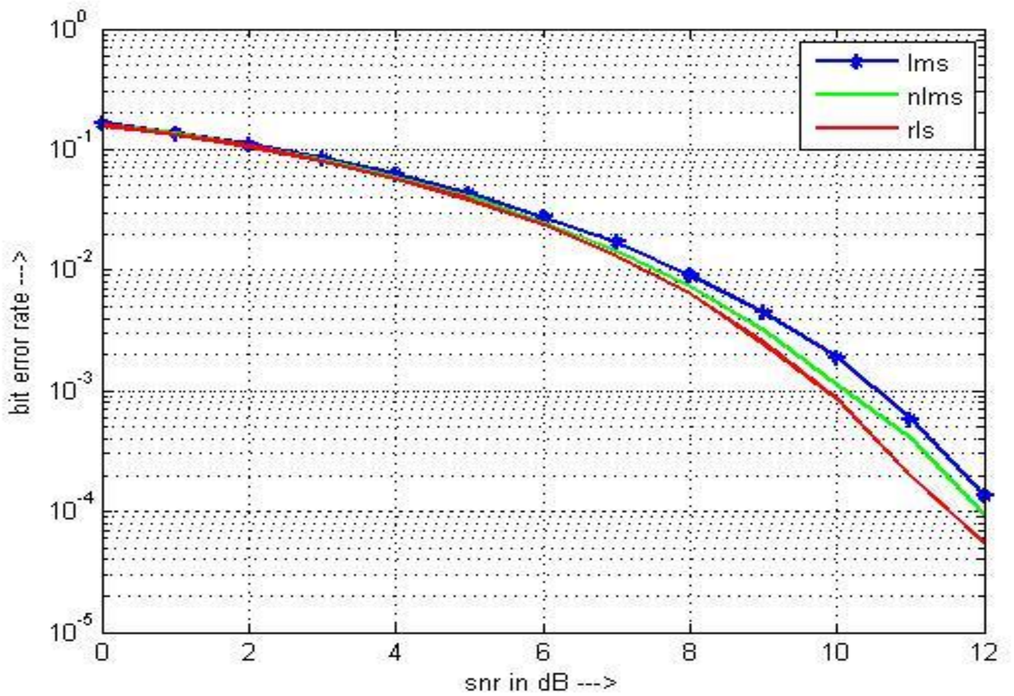


Fig 3.8 BER comparison for LMS, NLMS, and RLS

Fig 3.8 shows the BER performance comparison for LMS, NLMS, and RLS algorithm. BER performance for different algorithm has been compared and was found that RLS algorithm, has the best BER performance as compared to LMS and NLMS.

<u>Simulation Configuration:</u> Step size $\mu = 0.01$, Initial weight w=2.9, Number of channel taps=4, Fading parameter m=1.2 and Ω=2

3.5 Conclusion

In this chapter, different equalization techniques were discussed. As the step size μ increases the convergence rate of learning curve also increases i.e. the saturation in mean square error is achieved at a lower number of iterations, but one problem is that in case of higher convergence rate, mean square error is slightly greater. Decision feedback equalizer provides better performance than linear equalizer. RLS has better BER performance than LMS and NLMS.

In the next chapter, Implementation of pilot based OFDM will be discussed.

CHAPTER 4

Pilot Based OFDM

4.1 Introduction

Underwater Acoustic channel is very complex due to the non-homogeneity of the water. The constant motion of water and also the bottom and surface boundaries of channel make it more complex [19]. Due to these complex nature of underwater channel, many phenomena such as multipath, Doppler spread, Attenuation etc. occur. Multipath causes ISI, Doppler spread causes reduction in bandwidth and similarly many problems occur due to such effects making underwater communication very challenging [24]. To overcome such problems, OFDM can be implemented in underwater communication which has efficient bandwidth capacity and could also mitigate ISI effect through the insertion of cyclic prefix [16, 24]. But, the performance of simple OFDM in underwater is not good. Hence, pilot based OFDM has been implemented.

Channel estimation is also required before the demodulation of OFDM as the acoustic channel is time varying and frequency selective for an underwater communication system. There are various ways and channel estimation method to perform this [20]. It can either be performed by inserting pilots into all the subcarrier of OFDM symbols or by inserting pilots between subcarriers at some fixed regular interval [18]. The first one is called block type channel estimation and the second one is called comb type channel estimation. The block type channel estimation is best suitable for slow fading but comb type channel estimation is best suitable for fast fading channels. The channel estimation for block type is based on LS (Least Square) or MMSE (Minimum mean square error) estimator [21]. In comb type channel estimation, channel varies even from one OFDM block to another. The comb-type pilot based channel estimation technique involves some algorithms to estimate the channel and some interpolation techniques. Channel estimation techniques for comb type pilot based arrangements are LS and MMSE. MMSE has very high complexity as compared to LS but has better performance [22, 23].

There are various interpolation techniques such as linear interpolation, low pass interpolation, Gaussian interpolation, second order interpolation, spline- cubic interpolation as well as time domain interpolation. Second order interpolation provides better performance than linear interpolation. In this chapter, OFDM, and its channel estimation has been simulated taking into consideration some underwater acoustic channel parameters [17].

4.2 OFDM

Orthogonal Frequency Division Multiplexing (OFDM), is a signal modulation technique in which a high data rate modulating stream is divided into many slowly modulated closely spaced narrowband subcarriers, and hence, it is less sensitive to frequency selective fading. OFDM has been widely adopted by many Wi-Fi standards like 802.11a, 802.11n, 802.11ac etc. and also by cellular standards such as LTE/LTE-A, WiMAX etc. Now, OFDM has also been proved to be an efficient technique for highly frequency selective underwater acoustic channel.
OFDM is a form of multicarrier modulation which consists of a number of modulated carriers closely spaced to each other. When modulation is applied to the carrier, sidebands spread out either side. The signals are transmitted close to one another hence, there must be a guard band between them so that they can be separated at the receiver using a filter. But, in the case of OFDM, a guard band is not required as the signals are orthogonal to each other. This can be achieved if the spacing between the carriers will be kept equal to the inverse of the symbol period. The OFDM concepts can be explained by using FFT and IFFT in the digital domain.

In the digital implementation of OFDM system, the input bits are first grouped and then mapped to source data which is the complex number and is constellation point of modulation such as BPSK, QAM etc. These symbols are treated in frequency domain at the transmitter and the IFFT block transforms those data into time-domain.

OFDM has many advantages such as immunity to selective fading, efficient spectral efficiency, simpler channel equalization etc. But it also undergoes some disadvantages such as High peak to average power ratio and also it is sensitive to carrier offset.

4.3 Pilot based OFDM

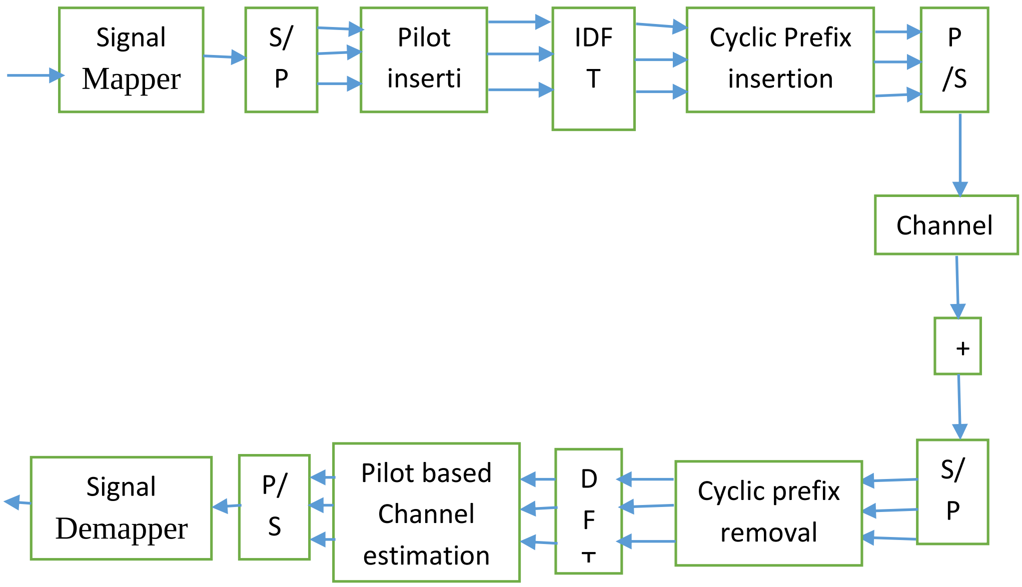


Fig 4.1 Block diagram of pilot based OFDM

The binary information is first mapped and combined through signal mapper. After that, it is converted to parallel data streams i.e. in the time-frequency domain. After that pilot is inserted either to all subcarriers or between subcarriers at a regular time period. After pilot insertion IDFT block transforms the data sequence in frequency domain into time domain signal as follows:

$$x(n) = IDFT\{X(k)\} \qquad n = 0,1,2, \dots \dots N-1$$

$$= \sum_{k=0}^{N-1} X(k) e^{j(2\pi kn/N)}$$

Where N is the length of DFT.

After IDFT block, the cyclic prefix is inserted in which last few bits are added to the start bits so as to remove the ISI effect.

Now, the OFDM symbol becomes:

$$x_f(n) = x(N+n), \quad n = -N_c, -N_c + 1, \dots \dots$$

$$= x(n) \qquad n = 0,1,2, \dots N-1$$

Where N_c is the length of the cyclic prefix.

Now the signal $x_f(n)$ has to be transmitted through frequency selective channel so it has to be converted into serial bit first hence parallel to serial converter is connected after cyclic prefix insertion block. After transmitted through channel, noise is added to it. Hence the received signal now becomes

$$y_f(n) = x_f(n) \otimes h(n) + w(n)$$

Where $w(n)$ is AWGN and $h(n)$ is the impulse response of the channel. The impulse response of the channel can be represented by

$$\sum_{i=0}^{r-1} h_i e^{j\frac{2\pi}{N}f_{d_i}T_n}\delta(\lambda - \tau_i) \qquad 0 \le n \le N-1$$

Where r is the total number of channel path, h_i is the complex impulse response of the ith path Doppler frequency shift, λ is delay spread, T is the time period and τ_i is the delay of ith path normalized by the sampling time. After receiving the symbol through channel it has to be converted into serial to parallel data. After that cyclic prefix has to be removed.

$$y(n) = y_f(n + N_c) \qquad n = 0,1,2, \dots \dots \dots . . N-1$$

Then y(n) is again converted into the frequency domain by passing it through DFT block.

$$Y(k) = DFT\{y(n)\} \qquad k = 0,1,2, \dots \dots \dots . N-1$$

$$= \frac{1}{N}\sum_{n=0}^{N-1} y(n)e^{-j(2\pi kn/N)}$$

Now we assume that there is no ISI,

$$Y(k) = X(k)H(k) + W(k)$$

Where $H(k)$ is the DFT of $h(n)$ and $W(k)$ is the DFT of $w(n)$.

After this pilot symbols are extracted and the channel is estimated through it.

The estimated channel is given by

$$\hat{X} = \frac{Y(k)}{H(k)} \qquad k = 0,1, \dots \dots \dots \dots \dots N-1$$

Now, through signal demapper, we obtain the binary data. Now, the comparison is made with the received data to transmitted data to estimate the error and BER performance is also computed.

4.4 Types of Pilot

Depending on the different types of pilot arrangement in time-frequency domain, there are basically three classifications as follows:

1. Block Type
2. Comb type
3. Lattice type

4.4.1 Block Type Pilot

Block type pilot arrangement is as shown below.

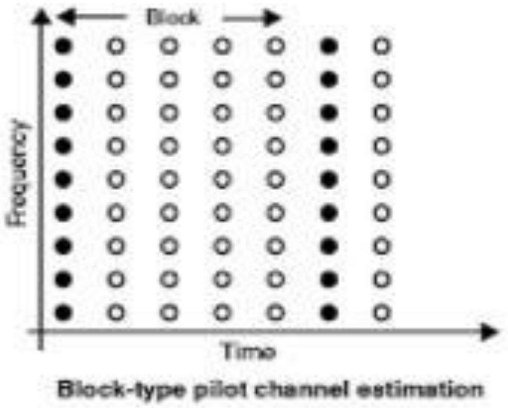


Fig 4.2 Block type pilot

In the block type pilot based OFDM, all subcarriers are transmitted at a regular interval for channel estimation. In this, pilot insertion is done in the time axis with all subcarriers as pilots, hence, we need time domain interpolation to estimate the channel. Let T_t denote the pilot symbol period in time domain. This symbol period should be less than the coherence time so as to track the effect of time variation of channel. Hence, symbol period must follow the following characteristics:

$$T_t \leq t_{coherence}$$

$$\leq \frac{1}{f_{doppler}}$$

Mostly for slow fading channel this type of pilot arrangement is used.

4.4.2 Comb Type Pilot

Comb type pilot pattern is as shown below:

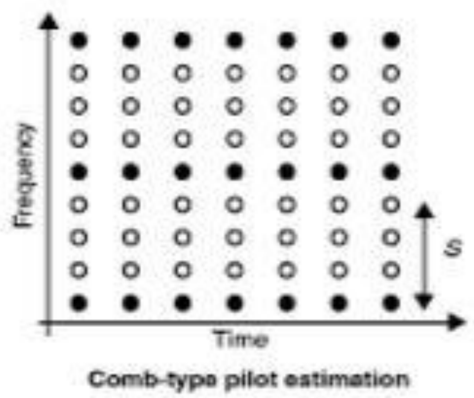


Fig 4.3 Comb type pilot

In the comb-type pilot arrangement, pilot subcarriers are inserted in the frequency domain at a certain interval. Hence, in this type interpolation is done in the frequency domain. Let T_f be the regular interval of pilot tones in frequency domain. In this case the period should be less than the coherence bandwidth so as to track the frequency selective fading characteristics as follows: $T_f \leq \frac{1}{\sigma_{max}}$

Mostly for fast fading channel this type of pilot arrangement is used.

4.4.3 Lattice Type Pilot

Lattice type pilot arrangement can be shown as:

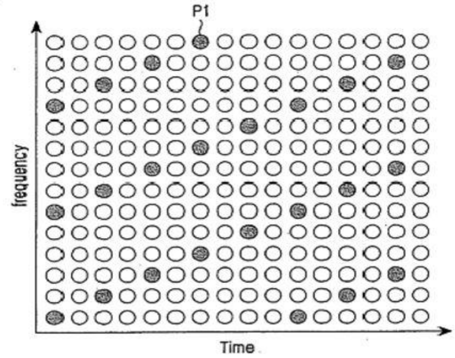


Fig 4.4 Lattice type pilot

In the comb type pilot arrangement, pilot tones are inserted in time as well as frequency axis. The time and frequency domain interval should follow the below inequalities so that it will keep track on time-varying nature of the frequency selective channel.

$$T_f \leq \frac{1}{f_{doppler}}$$

And

$$T_f \leq \frac{1}{\sigma_{max}}$$

Lattice type pilot arrangement can be used in case of slow as well as fast fading. For the underwater acoustic channel, lattice type based OFDM is the best suitable method as fading in underwater can be of any type. Performance depends on the spacing between pilots or pilot arrangement.

4.5 Channel Estimation

There are basically two channel estimation techniques:

1. LS (Least Square)
2. MMSE (Minimum Mean Square Error)

4.5.1 LS channel Estimation

In LS Channel estimation method, the estimate of the channel $\widehat{H}$ is found in order to minimize the cost function as follows:

$$J(\widehat{H}) = ||Y - X\widehat{H}||^2$$

$$= (Y - X\widehat{H})^H (Y - X\widehat{H})$$

After taking derivative of this function w.r.t H and equating it to zero, cost function is minimized and it gives the following solution:

$$\widehat{H}_{LS} = (X^H X)^{-1} X^H Y = X^{-1} Y$$

Suppose each component of the LS channel estimate $\widehat{H}_{LS}$ is represented by $\widehat{H}_{LS}[k]$, k=0, 1, 2…N-1

In case of ICI-free condition, X is supposed to be diagonal and the LS channel estimate for each subcarrier can be given as follow:

$$\hat{H}_{LS}[k] = \frac{Y[k]}{X[k]} \text{ , k=0, 1, 2,………N-1}$$

$$MSE_{LS} = E\{(H - \hat{H}_{LS})^H (H - \hat{H}_{LS})\}$$

$$= E\{(H - X^{-1}Y)^H (H - X^{-1}Y)\}$$

$$= E\{(X^{-1}Z)^H (X^{-1}Z)\}$$

$$= E\{Z^H (XX^H)^{-1} Z\}$$

$$= \frac{{\sigma_z}^2}{{\sigma_x}^2}$$

As MSE is inversely proportional to the SNR $\frac{{\sigma_x}^2}{{\sigma_z}^2}$, hence noise enhancement can take place, especially when the channel is having deep null.

4.5.2 MMSE Channel estimation

LS solution can be considered as $\hat{H}_{LS} = X^{-1}Y \cong \tilde{H}$

If W is the weight matrix, then we can define $\hat{H} \cong W\tilde{H}$ corresponding to MMSE estimate. Mean square error of the channel estimate $\hat{H}$ can be given as:

$$J(\hat{H}) = E\left\{||e||^2\right\} = E\{||H - \hat{H}||^2\}$$

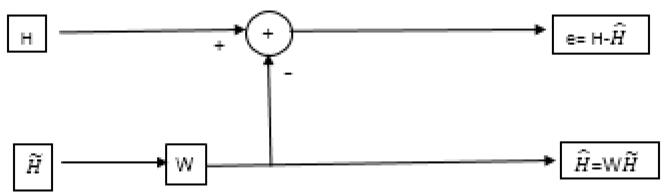


Fig 4.5 MMSE channel estimator

Thus, through MMSE channel estimator, a better estimate can be found in terms of W in a way so as to minimize MSE.

The MMSE channel estimator is as follows:

$$\hat{H} = W\tilde{H} = R_{H\tilde{H}} R^{-1}{}_{\tilde{H}\tilde{H}} \tilde{H}$$

$$= R_{H\tilde{H}} \left(R_{HH} + \frac{{\sigma_z}^2}{{\sigma_x}^2}\ \mathrm{I}\right)^{-1} \tilde{H}$$

4.6 Simulation Results and discussion

Fig 4.6 shows the BER performance comparison for OFDM with pilot and OFDM without a pilot. We can see that BER performance after using pilot is better than that without using a pilot. In this, no channel estimation has been done.

Simulation Configuration: m=1.5 and Ω=2, No of symbols = 10^4 , No. of subcarriers = 64, Length of cyclic prefix=16

Hence total length of 1 symbol transmitted = 64 +16 = 80 bits

In case of pilot, number of subcarriers= 52, no of pilots=12

Fig 4.7 shows the BER comparison for the different extent of fading i.e. for different value of m. In this, the pilot has been added and the comparison has been done by adding nakagami fading with a different value of m and also without fading. We can see that the BER performance is better for the greater value of m.

Simulation Configuration: Number of subcarriers= 52, no of pilots=12, Length of cyclic prefix=16, Hence total length of 1 symbol transmitted = 64 +16 = 80 bits

m= 0.7, 1, 1.5

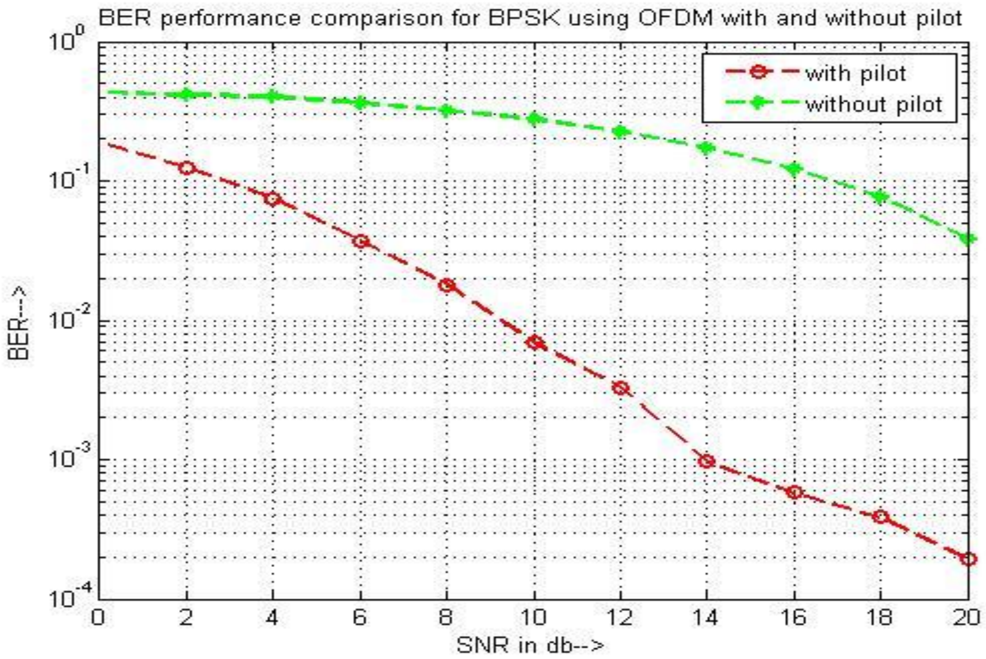


Fig 4.6 BER performance with pilot and without pilot (comb type pilot)

Fig 4.8 shows the BER performance comparison for the comb-type pilot arrangement. In this, LS channel estimation and linear as well as Gaussian interpolation method have been used. We can see that Gaussian interpolation technique has better performance than linear interpolation. There are various techniques with much better performance.

Simulation Configuration: Fading parameter m=1, Ω=1, No of pilots = 4 at subcarrier position of 1, 22, 43, 64. Total no of transmitted bits = 80.

Fig 4.9 shows the MSE for block type pilot based OFDM with LS and MMSE channel estimation technique. MMSE technique has proved to be better than LS channel estimation technique. LS channel estimation technique is very simple but MMSE has very high complexity.

Simulation Configuration: FFT size = 64

Channel Delay tap = [0.5 3.5]

Fig 4.10 shows the BER performance for LS and MMSE channel estimation technique in case of block type pilot. MMSE has better performance than LS.

Simulation Configuration: FFT size = 64

Channel Delay tap = [0.5 1.2 2.1]

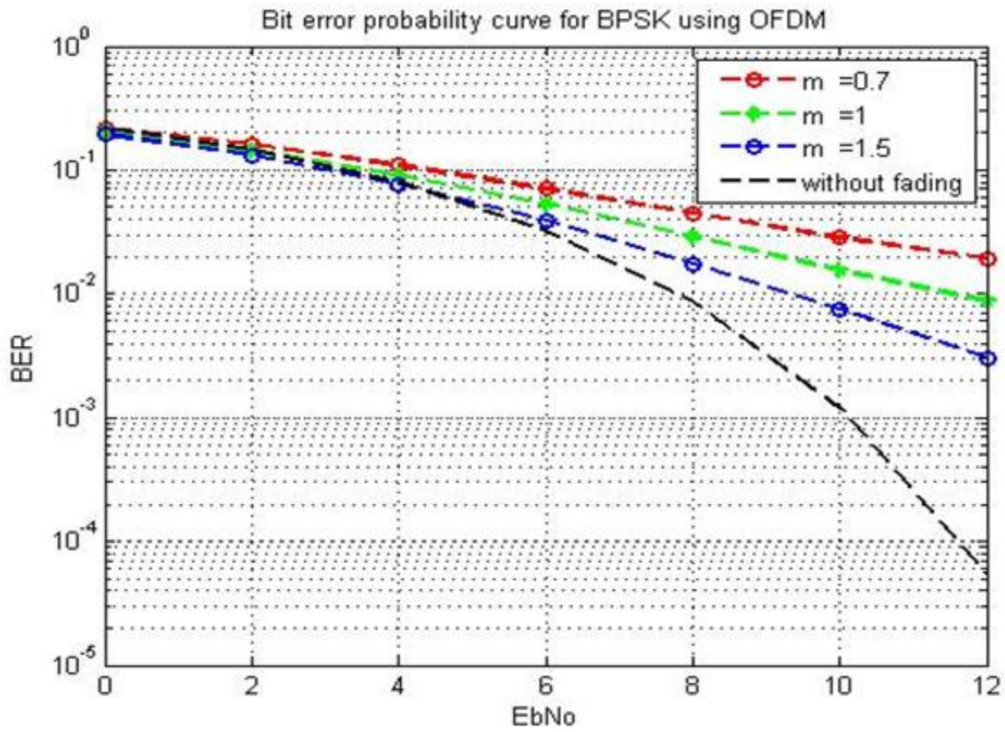


Fig 4.7 BER comparison for different value of m with comb-type pilot

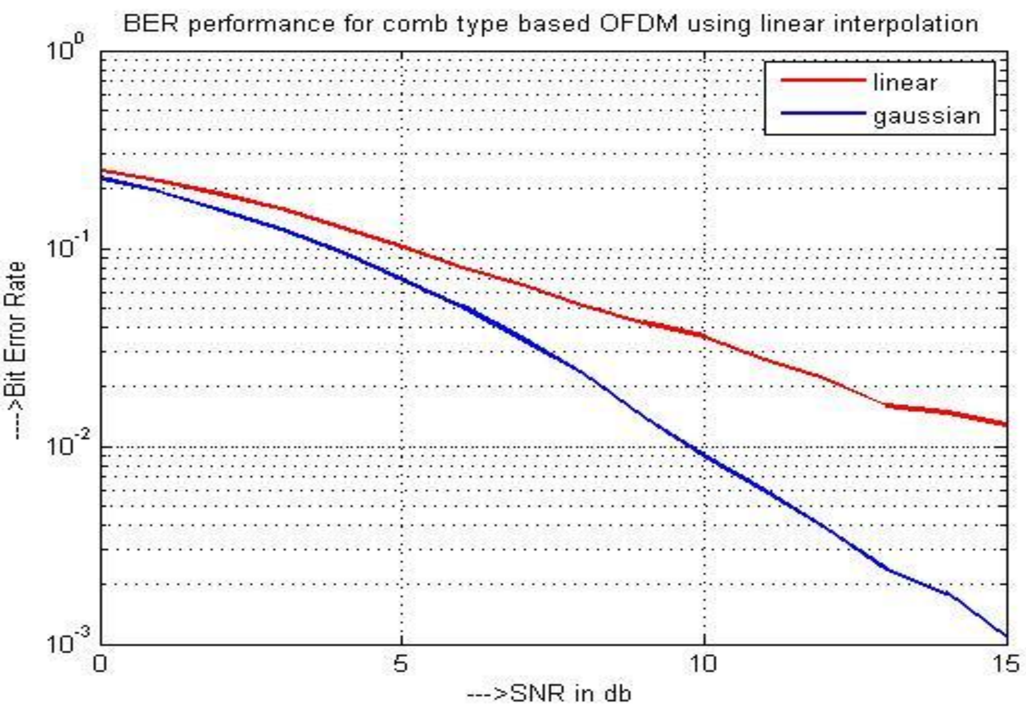


Fig 4.8 BER comparison for Comb type pilot with linear and Gaussian interpolation technique and LS channel estimation

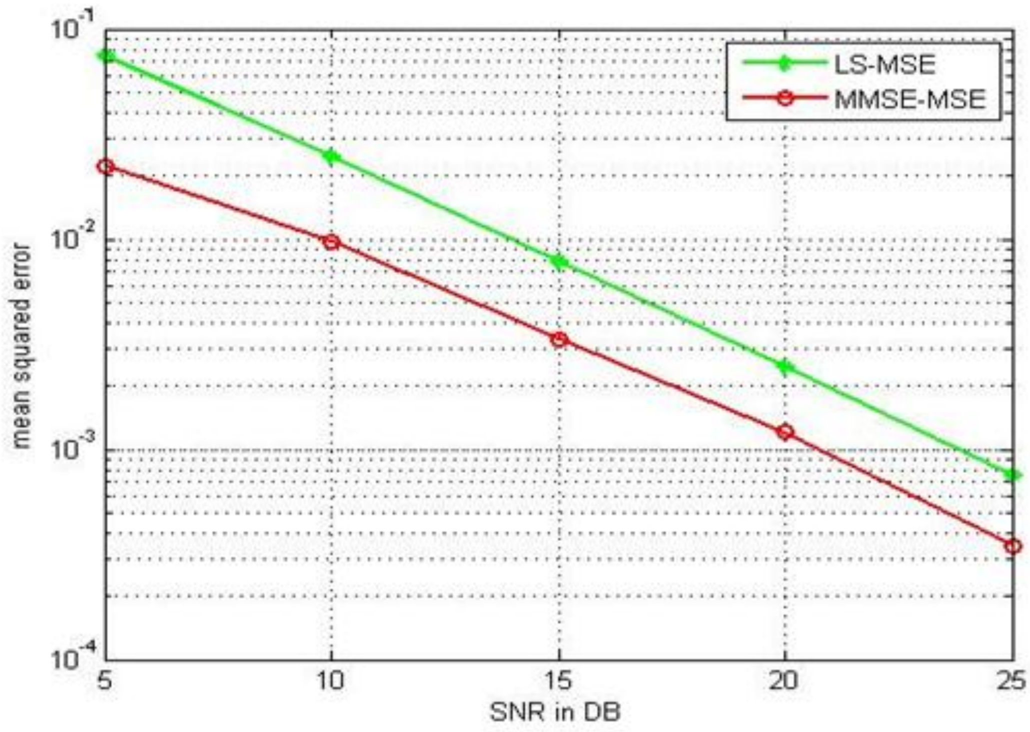


Fig 4.9 MSE comparison for LS and MMSE channel estimation in block type pilot based OFDM

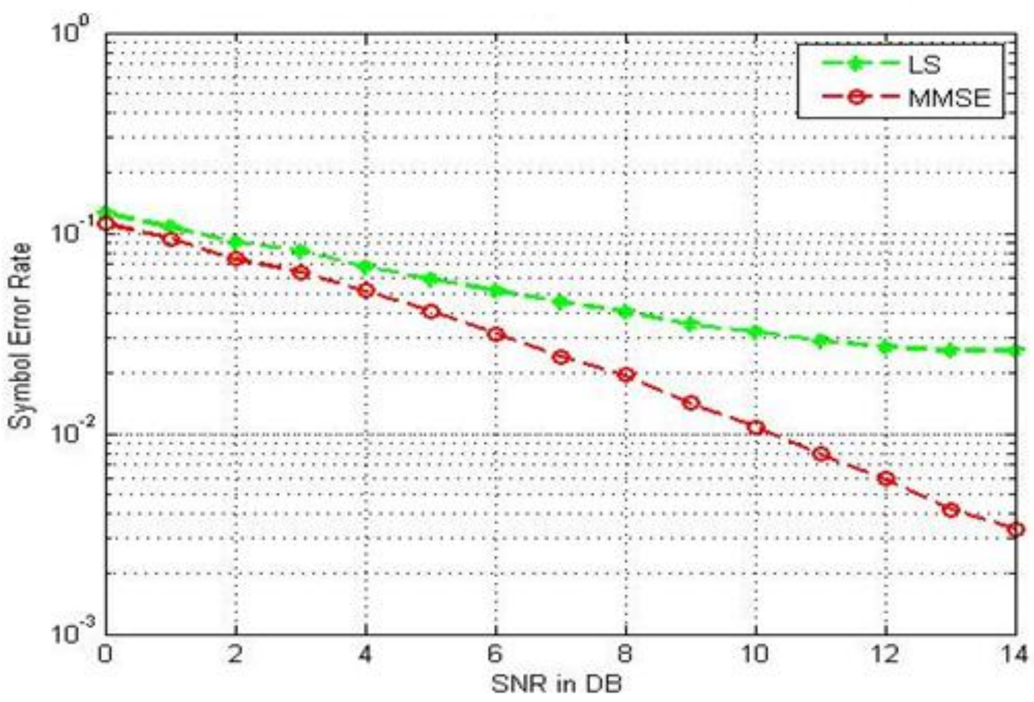


Fig 4.10 BER performance for LS and MMSE channel estimation in block type pilot based OFDM

4.7 Conclusion

In this chapter, implementation of Pilot based OFDM was discussed and following conclusions can be made. BER performance of OFDM after using Pilot is better than without using a pilot. OFDM with pilot has been implemented using nakagami fading with different parameter value (m=0.7, 1, 1.5) and can be seen that for the greater value of m, BER performance is better. MMSE channel estimation technique is better than LS estimation technique.

In the next chapter, implementation of LDPC coding will be discussed for underwater acoustic communication.

CHAPTER 5

LDPC Coding

5.1 Introduction

The underwater acoustic channel is very complex as it has severe frequency-dependent attenuation, long multipath delay, fast spatial and temporal variations etc. To overcome these problems and to ensure reliable transmission of data, channel coding technique is required [7]. LDPC code has better performance over all other coding techniques such as turbo code. In this paper, it can be seen that BER of 10^{-4} can be achieved at a very low SNR of 2.2 dB and at m=1.5 (nakagami fading parameter) which shows very good performance. It has low complexity than turbo code and Shannon capacity can be achieved through it [8, 10]. LDPC code of almost any code length and code rate can be generated. Due to many such advantages, LDPC code is the best suitable for underwater communication. For underwater, nakagami fading is being used [5] hence LDPC code has been implemented with nakagami fading and the BER performance for different fading parameter m and different code rate has been compared.

LDPC coding is a linear forward error correcting code and is a method for transmitting the message signal over the noisy channel. It was first proposed in 1962 in the Ph.D. thesis of Gallager at MIT. As the transmitted messages are in binary i.e. in the 0 and 1 form. The idea behind this forward error correcting code is to send the message bit with some extra check bits forming the code word for the message [8, 9]. These check bits are sufficiently distinct from each other such that at the receiver the transmitted messages can be easily inferred even when few bits of the code word changes during transmission across the channel [9].

5.2 Low-Density Parity Check Matrix

Low-density parity check matrix H contains a very few non-zero entity. As H matrix is sparse in nature so code length is directly proportional to decoding complexity.

If each code bit has fixed number of parity checks w_c, and each having fixed number of code bits w_r then the parity check matrix is called regular.

Parity check matrix H= $\begin{bmatrix} 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 & 1 \end{bmatrix}$ is called regular with $w_c = 2, w_r = 3$

For an irregular matrix H, the number of columns that are having weight i is represented by v_i and the number of rows having weight i is represented by h_i, then the combined set of v and h is known as degree distribution of the code.

In a regular LDPC code, H matrix has $m.w_r = n.w_c$, ones.

Also, an irregular H matrix has $m(\sum_i h_i.i) = n(\sum_i v_i.i)$ ones.

5.2.1 LDPC Construction

Few bits are allocated 1 in an all zero matrix to satisfy the required degree distribution in rows and columns and to form the binary LDPC code. In regular H matrix a row has w_c sets and each set contains M/w_c rows.

LDPC codes are represented graphically through tanner graph consisting two sets of nodes in which n nodes are for code word bits and m nodes are for check bits. The line which connects a check node to bit node is called an edge, therefore, total number of edges is same as the number of 1's in H matrix.

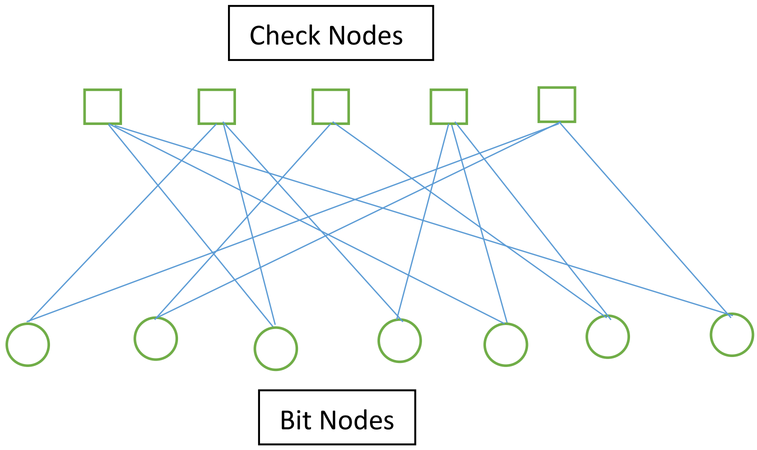


Fig 5.1 Tanner graph

5.3 LDPC Encoding

LDPC Encoding can be understood through the following example: Let us suppose that a code consists of 6 strings satisfying the parity check equation as follow:

$$c_0 \oplus c_2 \oplus c_3 = 0$$

$$c_1 \oplus c_0 \oplus c_4 = 0$$

$$c_0 \oplus c_1 \oplus c_2 \oplus c_5 = 0$$

Code word has following constraint in metric form:

$$\begin{bmatrix} 1\ 0\ 1\ 1\ 0\ 0 \\ 1\ 1\ 0\ 0\ 1\ 0 \\ 1\ 1\ 1\ 0\ 0\ 1 \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \\ c_2 \\ c_3 \\ c_4 \\ c_5 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

In the above equation, Parity check matrix $H = \begin{bmatrix} 1\ 0\ 1\ 1\ 0\ 0 \\ 1\ 1\ 0\ 0\ 1\ 0 \\ 1\ 1\ 1\ 0\ 0\ 1 \end{bmatrix}$. Each row of H forms parity check equation and each column represents a bit in the code word. Hence, H matrix is an $m \times n$ matrix with binary entries having m parity check equation and n code words.

A code word $y = [c_0\ c_1\ c_2\ c_3\ c_4\ c_5]$ is called valid only when it satisfies $Hy^T = 0$.

The above parity check equation can be re-written as :

$$c_3 = c_0 \oplus c_2$$

$$c_4 = c_0 \oplus c_1$$

$$c_5 = c_0 \oplus c_2 \oplus c_1$$

The message bits are c_2 , c_1, c_0 and parity check bits are c_5, c_4, c_3 . Again, this three constraint can be written in matrix form as follows:

$$[c_0\ c_1\ c_2\ c_3\ c_4\ c_5] = [c_0\ c_1\ c_2] \begin{bmatrix} 1\ 0\ 0\ 1\ 1\ 1 \\ 0\ 1\ 0\ 0\ 1\ 1 \\ 0\ 0\ 1\ 1\ 0\ 1 \end{bmatrix}$$

G= $\begin{bmatrix} 1\ 0\ 0\ 1\ 1\ 1 \\ 0\ 1\ 0\ 0\ 1\ 1 \\ 0\ 0\ 1\ 1\ 0\ 1 \end{bmatrix}$ is generator matrix. Suppose the message bits are $t = [t_1\ t_2\ t_3, \dots \dots . t_k]$ having k message bits. Hence, the code word c can be given by: $\boxed{c = t\ G}$

Code rate is given as $k/_n$ with message bits k and code word bits n.

A code containing message bits k has 2^k code words whereas the total length of binary vectors is 2^n. Gauss-Jordan elimination can be performed on H to obtain generator matrix G as follow:

$$H = [F.I_{n-k}]$$

Where F is a binary matrix having size $(n-k) \times k$ and I_{n-k} is the identity matrix having order $n-k$. The Generator matrix G can be written as $G = [I_k, F^T]$. Rows of G is orthogonal to H such that $GH^T = 0$

5.4 LDPC Decoding

The classes of decoding algorithms are collectively called message passing algorithm as its operations are explained through tanner graph by passing messages along the edges of the graph. LDPC decoding is also called iterative decoding algorithm because in this algorithm messages are passed iteratively forward and backward between the bit and check node till the result is achieved. Each iteration includes two basic steps: check and variable node processing. In each iteration, information is received by each and every check node from neighboring node and after processing, they are again sent back to that node.

There are mainly two LDPC decoding algorithm: Hard and Soft decision algorithm. There are various decoding algorithms based on the complexity and performance.

5.4.1 Hard Decoding Algorithm

Bit flipping Algorithm It is a hard decision algorithm for LDPC decoding. In this, detector takes hard binary decision for each bit it receives and passes it to the decoder. In the tanner graph, a bit node sends a message about the bit whether it is 0 or 1, and each check node also sends a message to bit node connected to each other, sending the information available at each check node.

The check node finds the modulo-2 sum for each incoming bit and checks if it satisfies the parity check equation or not. The bit node inverts its value if most of the message bit is found to be different from the received bit. This process repeats itself till all the parity check equations are satisfied.

It has two main advantages:

1. Once a solution has been found, additional iterations are avoided.
2. It always detects a failure if it is not able to find the code word.

The basic principle of bit flipping algorithm is that a bit which is involved in many incorrect check equations is incorrect itself. Due to the sparsity of H, parity check equations contain a different set of code word bits.

5.4.2 Soft Decoding Algorithm

Soft decision decoding technique gives enhanced performance than hard decision decoding as in this case we take the probabilities of occurrences of received bit that whether received bit is 0 or 1.

Sum-Product Decoding

This is a soft decision message passing algorithm. Bit-flipping decoding makes a hard decision about the bit received whereas Sum-Product decoding accepts the probabilities of occurrence of received bit as 0 or 1. The probabilities of the bit received should be known in advance at the receiver side hence called prior probabilities. The probabilities of the bit after passing through the decoder are called posterior probabilities. In this decoding technique, the probabilities are represented in the form of log-likelihood ratios. We can easily find probabilities for the bit 1 and 0 i.e. $p(x = 1)$ and $p(x = 0)$ in the case of binary values, as we know $p(x = 1) = 1 - p(x = 0)$ hence we have to know only one probability. Log likelihood ratios can be represented by a single value as

$$L(x) = \log\left(\frac{p(x = 0)}{p(x = 1)}\right)$$

If $p(x = 1) < p(x = 0)$ then $L(x)$ is +ve and the bit is 0, the difference between these probabilities gives the measure of correctness about the bit to be 0.

Similarly, if $p(x = 0) < p(x = 1)$ then $L(x)$ is -ve and the bit is 1, the difference between these probabilities gives the measure of correctness about the bit to be 1.

Thus the sign of $L(x)$ tells about whether the bit x is 0 or 1 and the magnitude tells the reliability of the decision.

5.5 Simulation Results and discussion

Fig 5.2 shows the Impact of the decoding techniques (Soft and Hard decision decoding). In the case of a soft decision, we get better BER performance as compared to hard decision decoding i.e. at same SNR value, bit error rate for soft decision decoding has a lower value as compared to hard decision decoding.

Simulation configuration: Length of message bits = 168, Length of code bits = 168, Hence, total length of transmitted bits= 336, Code rate= ½, Nakagami fading parameter m= 0.7, No. of iterations = 5, No. of frames= 10, No. of ones per column = 3, No. of ones per row = 6.

Fig 5.3 shows BER performance comparison with the different value of parameter mu with nakagami channel fading. As the value of m increases the extent of fading decreases hence the BER performance gets improved. For m=1, the fading is Rayleigh fading and for $m > 1$, the fading is Rician fading.

Simulation configuration: Length of message bits = 168, Length of code bits = 168, Hence, total length of transmitted bits= 336, Code rate= ½, No of iterations = 5, Decoding technique- Log-domain

Fig 5.4 shows BER Performance comparison for different modulation technique with nakagami channel fading. Fig shows the BER performance of BPSK, QPSK, and 16-QAM. We can see that BER performance of BPSK and QPSK is same and better than 16-QAM.

Simulation configuration: Taken same values as in above simulation.

Fig 5.5 shows the comparison of BER performance for a different code rate of LDPC. It is shown that lower the value of code rate, better will be the performance. BER for different code rate values 1/2, 2/3, 3/4 and 4/5 has been compared and it can be seen that BER performance with code rate 1/2 is the best among all.

Simulation configuration: Taken same values as in above simulation

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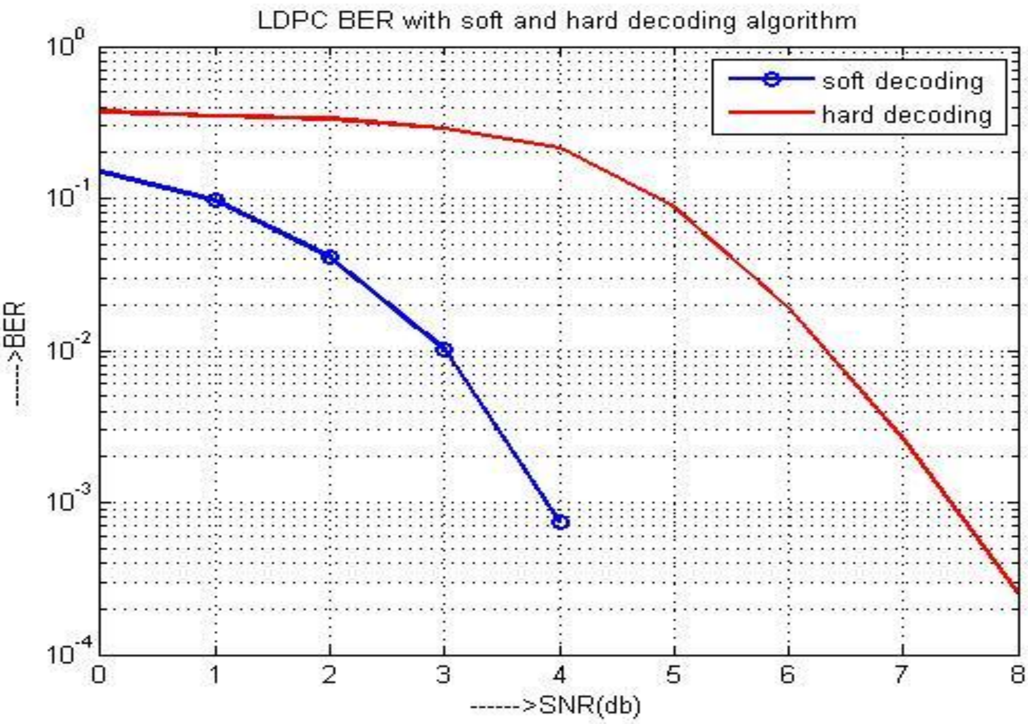

Fig 5.2 BER performance for Hard and Soft decision decoding technique

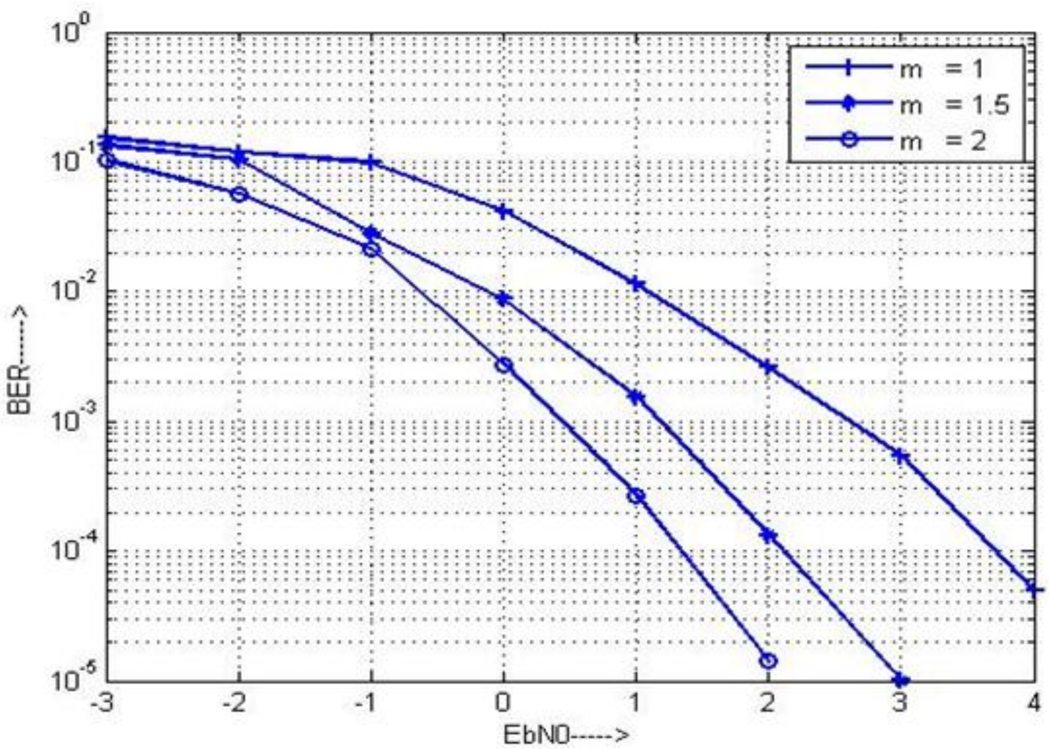

Fig 5.3 BER performance for BPSK Modulation with nakagami channel fading

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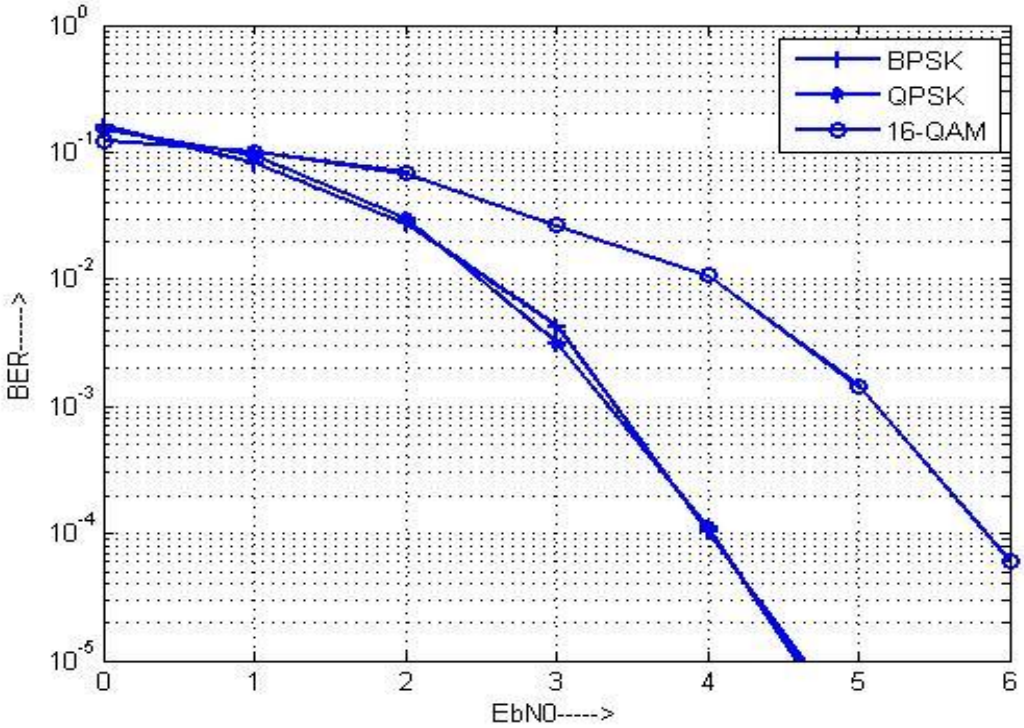

Fig 5.4 BER performance for different modulation technique using LDPC

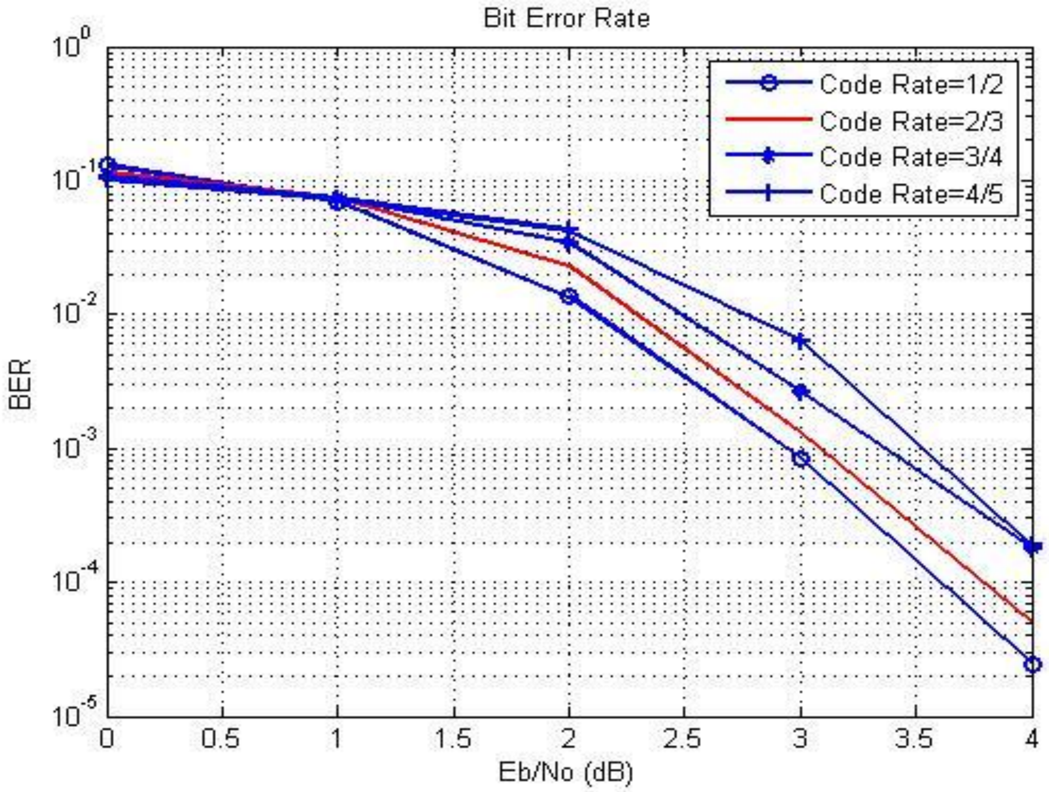

Fig 5.5 BER performance comparison for different LDPC code rate

5.6 Conclusion

In this chapter, LDPC coding technique was discussed and following conclusions can be drawn based on the implementation result. Soft LDPC decoding technique has better performance than hard LDPC decoding technique. LDPC with nakagami fading (m=1, 1.5, 2) has been implemented and at very low SNR, BER of the order of 10^{-4} has been achieved. Different modulation techniques (BPSK, QPSK, and QAM) also have been implemented using LDPC and it can be seen that BPSK and QPSK have same BER performance as it is theoretically known. Now, LDPC with different code rate (1/2, 2/3, 3/4 and 4/5) has been implemented and by comparison, it can be seen that low code rate provides better BER performance.

Next chapter is the last chapter of the thesis and contains conclusion and future work of the project research.

CHAPTER 6

Conclusion and Future Work

6.1 Conclusion

For underwater communication, Acoustic wave is the only mean for transmission up to a distance over 100m as radio wave undergoes very high attenuation and optical wave travels to very short distances. But underwater acoustic channel undergoes many problems such as limited bandwidth, path-loss, Doppler spread and long propagation delay. Also, after studying about channel modelling and fading characteristics inside water, it has been concluded that there are various extents of fading at various environmental conditions, hence nakagami fading can be used inside water as it is the generalized type of fading in which by setting the value of parameter m we can have different extent of fading. For the underwater acoustic channel, generalized noise model has not been developed till now.

Taking channel fading as nakagami and noise as AWGN, various techniques in acoustic underwater communication has been implemented which can be used for radio communication to enhance the performance. Equalization, OFDM as well as LDPC Coding has been implemented. First of all, different equalizer techniques (LMS, NLMS, and RLS) were implemented and it was found that RLS is the best equalizer algorithm. Also, as the RLS adaptively updates the weight coefficient at each iteration hence it is the best suitable for underwater communication because of the varying nature of the acoustic channel. After that, OFDM was also implemented. For OFDM, by setting the pilot interval according to the value of coherence time and coherence bandwidth existing inside water and using lattice type pilot, performance can be enhanced in the case of underwater acoustic communication. LDPC Coding has been done by taking nakagami fading and the result has been discussed. Through LDPC, BER of the order of 10^{-4} has been achieved at low SNR value. Different LDPC decoding techniques have also been implemented and their performance has been compared. Hence, the techniques having better performance can be used for underwater acoustic communication.

6.2 Future Work

Based on this thesis, some of the areas having scope for future research are as follows:

1. Comb and block type pilots have been implemented but lattice type pilot can also be implemented which has the best performance than these two type.
2. Some generalized noise modeling can be done and can be implemented with these techniques to check the differences in performance.
3. All the techniques have been implemented separately, we can combine any of these techniques to get the enhanced performance.
4. MIMO can also be implemented for underwater communication and it can also be combined with OFDM and LDPC coding to get the better result.
5. Underwater acoustic sensor network is an emerging technology consisting of a number of sensors and vehicles deployed to perform collaborative monitoring task over a given area.

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